UNIVERSITY OF NEWCASTLE UPON TYNE

OPTIMISATION FOR PRODUCT AND PROCESS IMPROVEMENT: INVESTIGATION OF TAGUCHI TOOLS AND GENETIC ALGORITHMS

BY
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Dedicado

A mi madre

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As with any investigation of this extent, a large number of people supported the completion of this thesis. Nevertheless, more important than the number of people is that those contributions came from Top-Quality people.

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I think I got you all, but if I have missed anyone please forgive me (just blame it on the stress of writing this work up!).

DECLARATION

This thesis describes work carried out by the author in the Department of Mechanical, Materials and Manufacturing Engineering of the University of Newcastle Upon Tyne, United Kingdom, during the period September 1996 – September 2000 under the supervision of Dr. A. Anderson.

This thesis describes original work which has not been submitted for a higher degree at any other University and is the work solely of the undersigned author, except where acknowledged in the text.

Inti E. Garzon

ABSTRACT

Despite criticisms of its methodology, the Taguchi philosophy for quality improvement is generally applauded. Though originally intended to primarily achieve its results "off line", during the product design phase and before manufacturing, it has frequently also been deployed to solve problems "on line". Taguchi identifies the crucial design phases as "system design" and "parameter design", and his statistically-based tools are directed at the latter. The general objective of this investigation is to study two contrasting approaches to product and process optimisation, ie Genetic Algorithms, which may be appropriate to both "system design" and "parameter design" phases, with Taguchi and related statistical tools which may be appropriate to the "parameter design" phase.

The literature review concentrates on the up and downsides of Taguchi Methods, focusing on the philosophy and methodologies. Its statistical content, particularly related to the use of Signal-To-Noise ratios and saturated fractional factorial designs, have widely reported deficiencies. In order to evaluate and, if necessary, overcome these deficiencies, a combination of Taguchi and non-Taguchi tools are brought into an experimentation strategy to determine robust methodologies that contribute to enhanced product performance. The approach is motivated from a design for quality standpoint and is directed principally at improving performance.

The approach is illustrated using three case studies in surface finish from metal cutting and simulation systems optimisation. These case studies involve a variety of experiments different in nature, from real physical experiments to

computer-based ones, and tackling a wide range of different problems such as: surface finish in milling and turning machining (metal cutting), optimum travel time and traffic junction control (transport traffic simulator) and out-of-balance-force problem (optimisation of simple Genetic Algorithms).

The study of Taguchi tools is an extension of previous work by Taher (1995). Some of his investigations are extended, principally the reliability of Taguchi saturated fractional factorial arrays, the need for factor/level analysis, criticisms of the Taguchi Signal-to-Noise ratios and the use of sequential experimentation. In addition to these, attention is focussed on the use of repetitions within the Taguchi methodology, the use of transformations or Generalised Linear Models and the possibility of using robust statistics.

The adoption of a sequential experimentation approach leads to a successful use of predefined Taguchi arrays influenced by user knowledge of confounding and interaction effects on main factors. From a global viewpoint, Factor/Level analysis is highly recommended. It is also determined that the reliability of results is highly affected by the use of Signal-to-Noise ratios, and alternative dispersion control tools are strongly advised. Taguchi's robust design methodologies are of value but require integration with other design and quality assurance methodologies, such as Concurrent Engineering and Quality Function Deployment.

The optimisation of a simple Genetic Algorithm (for the out-of-balance-force problem) is used as one test case for the investigation of Taguchi tools. However, this investigation is itself of interest for the general use of genetic algorithms as it addresses issues such as appropriate population size and choices for crossover and mutation modes and probabilities. Many previous investigations of these have only been of the "one factor at a time" type.

Nomenclature

θ	Complexity decomposable function (Salomon, 1995a)
ω	Rotational speed of rotor (rad/s)
Adj MS	Adjusted means of squares
Adj SS	Adjusted sums of squares
ANOVA	Analysis of variance
C	Coolant (factor, Chapter 3).
CG	Convergence Generation (generation in which GA first converged)
CL	Number of cuts (factor, Chapter 3).
CP	Controller Type (factor, Chapter 4).
CR	Convergence Rate (Eq. 5.6)
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CNC	Computerised Numerical Control
D_i	Delay time for replication *I* (Eq. 4.1)
DC	Depth of cut (factor, Chapter 3).
DIC	Direction of cut (factor, Chapter 3).
DF	Degrees of Freedom
DoE	Design of Experiments
F	F value for testing the hypothesis during ANOVA
F	Force (N)
F_i	Force (N) for each individual magnet (Eq. 5.1)
FF	Full factorial
F_x	Component x of force F (N) (Eq. 5.2)
F_y	Component x of force F (N) (Eq. 5.3)
$F(y)$	Data y transformed through SNR
GA	Genetic Algorithm
GENALG	Genetic Algorithm software (Anderson and Simpson, 1996)
GLM	Generalised Linear Model

HGV	Heavy Goods Vehicles
k	Constant (includes monetary terms) (Eq. 2.1)
L	Loss function (Eq. 2.1) (in monetary terms)
L_8	Taguchi's L_8 *array*
L_{16}	Taguchi's L_{16} *array*
L_{18}	Taguchi's L_{18} *array*
L_{32}	Taguchi's L_{32} *array*
LG	Linear graphs
LRT	Light Rail Transit
LTB	Larger-the-Better SNR
m	point at which the characteristics should be set (Eq. 2.1)
m_i	Individual magnet mass (kg)
MAXGEN	Number of generations/iteration (factor, Chapter 5).
MUTPRO	Mutation probability (factor, Chapter 5).
n	problem's dimensionality
OOBF	Out-Of-Balance-Force
$p>F$	Probability of rejecting the hypothesis (ANOVA)
P_c	Crossover probability (factor, Chapter 5).
P_m	Mutation probability (factor, Chapter 5).
PM1	Profile 1 Magnitude (factor, Chapter 4).
PM2	Profile 2 Magnitude (factor, Chapter 4).
PM3	Profile 3 Magnitude (factor, Chapter 4).
PS1	Profile 1 Slope (factor, Chapter 4).
PS2	Profile 2 Slope (factor, Chapter 4).
PS3	Profile 3 Slope (factor, Chapter 4).
POPSIZE	Population size (factor, Chapter 5).
QFD	Quality Function Deployment
R_a	Surface roughness using centre line average method
R_g	Distance to centroid (m)
$(R_g)_x$	Component x of R_g (m) (Eq. 5.2)
$(R_g)_y$	Component y of R_g (m) (Eq. 5.3)
R_q	Surface roughness using root mean square average

R_z	Surface roughness using ten point peaks to valley height average
RotChr	Rotating Chromosome
RSM	Response Surface Methodologies
SAS	Statistical Analysis Software
Seq SS	Sequential sums of squares
SD	Speed Distribution (factor, Chapter 4).
SNR	Signal-to-Noise ratio
SOM	Shift Operation Mutation
STD	Standard deviation
STB	Smaller-The-Better SNR
T	Tool type (factor, Chapter 3).
TS	Tool speed (factor, Chapter 3).
TOURN	Tournament size/winners (factor, Chapter 5).
V_i	Number of vehicles for replication i (Eq. 4.1)
VISSIM	Traffic flow simulator (PTV, 1997)
VM	Vehicle Mix (factor, Chapter 4).
WS	Workpiece speed (factor, Chapter 3).
x	Point at which the characteristic is actually set (Eq. 2.1)
XOVER	Crossover probability (factor, Chapter 5).
y	Data to be transformed by SNR

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Chapter 1
Introduction

Since the evolutionary quality philosophies introduced by Deming and Juran (Halberstam, 1984), few significantly different approaches to quality improvement arose until the appearance of Taguchi's philosophy (Taguchi 1986, 1987 and 1993) in the 1960s. Taguchi's approach for quality by design passed virtually unnoticed for most players in Western industry until the early 1980s (Ealy, 1988) when insiders rediscovered its powerful capabilities and "novel" techniques. Taguchi's approach comprises in one package a philosophy giving support to a group of tools conceived for designing quality into products. Taguchi's way of building that quality is by achieving robustness and reducing the effect of variation on product performance (Ross, 1988; Peace, 1993).

In recent years, the ways product and process development are done have undergone great changes, driven not only by the influence of new technologies but also by the increasing use of Design of Experiments (DoE) methodologies in the research and development stages. Together with DoE, the application of Taguchi methods has been attributed with the improvement of product and process developments to the point that their adoption by the engineering community is increasingly routine (Ealy, 1988). As this level of industrial acceptance increased, debate started to arise (see Kackar, 1985; Barker *et al,* 1989; Nair, 1986) on whether some Taguchi tools were robust enough for delivering top quality products. The debate has left some outstanding issues concerning the statistical methodologies behind Taguchi tools, especially those tools that are fundamental within his "recipe" (such as Signal-to-Noise ratio, Orthogonal Arrays and Inner-Outer arrays) (eg Kackar, 1985; Box, 1988; Nair, 1986; Wu, 1992). Apart from carrying out an extensive investigation on the conceptual part of Taguchi methods in relation to engineering design methodologies, Taher (1995) revisited some of the issues by a pragmatic engineering approach, comparing full factorial and sequential experimentation with Taguchi tools in order to identify those parts of Taguchi's methodology which appeared to work well in practical engineering situations. The present work aims to extend Taher's (1995) study within a similar framework. By considering additional case studies (and exploiting some of Taher's data) the robustness of his conclusions can be tested.

Despite the intention that Taguchi methods are generally to be used for optimising product design (Celik and Burnak, 1998), his approach falls short for addressing the multi-response optimisation problems which are characteristic of engineering design (Vining and Myers, 1990; Hendrix, 1991). Nowadays, the complexity of products may require the implementation of tools such as QFD (Clausing, 1990) for incorporating and satisfying customer requirements. Studies linking QFD and Taguchi methods can be found in the literature (Clausing, 1990; ASI, 1994; Taher, 1995) and are proof of the adaptability of some of Taguchi's concepts. Though standard Taguchi design strategies do not support sequential experimentation or multi-response optimisation (Bisgaard, 1993), Taher (1995) suggested that Taguchi tools can be integrated into alternative sequential experimentation strategies.

This study, therefore, does not intend to investigate the statistical concepts behind the Taguchi approach but rather to explore the issue of whether there is a "safe" or robust approach for the application of Taguchi tools to product optimisation. The approach in this study will be done from an engineering perspective (as Taguchi does), ignoring statistical issues such as any apparent links between responses within the data. This is not to deny the responsibility for reckoning the relative importance of this action and the dangers of accepting results without considering the nature of the patterns within the data. Within the manufacturing context, the general objective of this study is to investigate experimentally the use of Taguchi tools and novel optimisation techniques, such as Genetic Algorithms, for product and process improvement:

a) Identify potential issues related to the application of Taguchi methods and Genetic Algorithms within an engineering context.
b) An approach for product optimisation based on the combination of Taguchi and non-Taguchi tools, as suggested previously by Taher (1995).
c) Practical recommendations for the implementation of Taguchi methods and Genetic Algorithms in product and process improvement environments.

After a thorough literature review (Chapter 2), in order to fulfil the objectives proposed above, this study aims to provide answers to basic questions such as:

1) Is it actually possible to find parameters which reduce dispersion without affecting the mean as required by Taguchi's approach? While the other issues below have been widely raised in the literature, this one has not.
2) Is Taguchi's Signal-to-Noise ratio an appropriate metric to measure dispersion? Or, are there alternative statistical measures or techniques which provide better information about dispersion?

3) Are the Taguchi arrays appropriate in practice? Are there effective ways to use Taguchi arrays?

4) Does it help to bring in other Taguchi tools, such as linear graphs and confirmation runs?

Other important Taguchi tools, like Inner/Outer arrays, Loss Function and interaction tables, which complete the set of his seven most important tools (Ross, 1988; Lochner and Matar, 1990; Condra, 1995; Fowlkes and Creveling, 1995; Taher, 1995), are not studied in depth here. Taher (1995) has previously investigated both Inner/Outer arrays and Loss Function while linear graphs fulfil a similar function to interaction tables.

In order to fulfil the proposed objectives the study will look at three case studies involving typical engineering problems, in addition to the previous three case studies investigated by Taher (1995). Criteria for selecting these case studies involved the following considerations:

(i) The study should include at least one case study from each of the two types of experiments available: physical and simulated. Taher (1995) used three physical experiment case studies. Simulated experiments have especial significance as many product design activities nowadays make use of simulations for rapid prototyping and lower costs. Also, Taguchi applications to simulated experiments are relatively uncommon as most efforts have been directed (until now) towards physical experimentation (eg Bendell *et al,* 1989).

(ii) The idea is to select case studies addressing different problem types. Diversification of the problem type should give more robustness to the study.

Taher (1995) studied two brittle material mixture problems and one metal removal process (turning). The choice of another metal removal process (milling) as a case study here establishes a link with Taher's work. Adopting two simulation case studies in addition to this ensured the necessary diversity.

(iii) Resource availability was a significant factor. The fact that substantial computational facilities were available influenced the idea of working on simulation environments. Manufacturing facilities for the three main metal cutting processes (milling, turning and grinding) were also available to this study but the time constraint on physical experiments suggested that only one of these be investigated.

(iv) Variability within the case study is an important issue as it is one of the main concepts relating to the application of Taguchi Methods. Among physical experiments, metal cutting processes are known as great sources of variability, which hints at their suitability for the purposes of this study. Though in principle variability in deterministic simulations is almost non-existent (Belavendram, 1992), there is a whole class of non-deterministic simulations, such as the heuristic optimisation methods (which include Genetic Algorithms), which are based on processes involving random number generation and probability. "Variations" can be "induced" by changing the initial seeds required to generate random numbers and, therefore, to obtain different values (repetitions) each time.

Based on these premises, two simulated (traffic flow simulator and Genetic Algorithm parameter optimisation) and one physical (milling machining) experiments were selected (Table 1.1). Selecting the metal cutting experiment was a resource conscious decision. As has been pointed out in (ii), the need for a variety of cases allowed only one of the metal removal processes to be chosen, which means choosing between milling and grinding (turning has been studied by Taher (1995)).

In order to assess the investigation of Taguchi tools, an overall experimentation strategy (Fig. 1.1) was designed, which includes a general framework methodology (Chapter 3) to standardise the statistical evaluation of the case studies. The strategy starts by applying the general framework methodology to each one of the case studies from which two outputs are going to be obtained (Fig. 1.1). The framework methodology will use the experiment design to address the problem itself and to evaluate the Taguchi tools.

In this study, the application of statistical methodologies to problems will be done progressively. From the experiment design side, full factorial and Taguchi arrays will be introduced and compared on each one of the first three case studies (Chapters 3, 4 and 5) to reinforce and extend the previous investigation of Taher (1995). In Chapter 6 the focus will be on consolidating the investigations of Chapters 3-5, with the data from full factorial designs and Taguchi arrays evaluated in Chapters 3, 4 and 5. Though each case can and will be considered individually, making use of conventional statistical analysis techniques (eg ANOVA, GLM, main factor and interaction dot-line plots, Pareto charts) to process and analyse the data obtained through the use of those arrays will complement the set of tools for carrying out this investigation. The full factorial designs were used to compare design types (full factorial and Taguchi) and, at the same time, to study their integration with some variance reduction tools.

Unfortunately, there is no room for evaluating Taguchi's Inner-Outer arrays due to the problem types of the selected cases, though Taher (1995) has previously attempted this.

Prior to the actual case studies, Chapter 2 elaborates a comprehensive literature review regarding the operational side of the Taguchi approach. A brief description of the Taguchi philosophy covering his contributions, principles and basic tools is outlined there. The inclusion of a balanced survey of praise and criticism of Taguchi methods marks this Chapter as the starting point for the evaluation of Taguchi tools. The survey also collects a group of well-known "conventional" statistical tools (such as repetitions, randomisation and blocking), suggestions made by statisticians to overcome issues presented with Taguchi tools (for instance transformations) and a quick glance at more sophisticated tools for experimentation like robust statistical estimators. With the foundation given by Chapter 2 and the assistance of the framework methodology, the application of all these tools on each one of the next three case studies (Chapters 3, 4 and 5) will measure location and dispersion effects on the responses under investigation in each case. Metrics for measuring these effects will be mean, standard deviation and Signal-to-Noise ratio (SNR) (Smaller or Larger-the-Better as required), with the addition of some others on an individual case basis.

Chapter 3 will investigate the production of surface finish in milling processes, which will aim at determining, with the help of DoE techniques and/or Taguchi methods, factors affecting the production of fine surface finish as ways of quality improvement. Both 2-level full factorial designs and equivalent L_{16} Taguchi arrays (using Smaller-the-Better SNR) will be used. Two other additional comparisons will be made in this case study regarding both the process itself and the Taguchi tools investigation. On the process side, two methods for assessing surface finish, parallel and perpendicular to the direction of cut, will be compared to determine their possible effects on variation. On the Taguchi tools side, two types of linear graph specific for the Taguchi L_{16} will be compared to weigh up their effects on identifying factor and level significance.

Chapter 4 will study the effects of delay in traffic flow for a three-leg junction through the VISSIM (PTV, 1997) simulation environment. Experiment design for this case study compares both full factorial and the equivalent L_{32} Taguchi arrays using Smaller-the-Better SNR. The large number of variables for investigation in this case study offers a great opportunity to show up the capabilities of Taguchi arrays for shorter experimentation.

In Chapter 5 the investigation will lead to the other main path of this study: Genetic Algorithms (GA). The study of GAs will focus first on attempting the optimisation of their basic and most common parameters/operators. A typical engineering problem, the Out-Of-Balance Force (OOBF), will be the object of the GA implementation. This combinatorial problem is expected to push the GA to the limit, as it is among the most difficult problem types to solve for GAs. Continuing with the similar methodology, this case study will compare outcomes from both full factorial designs and the equivalent L_{16} Taguchi array.

After reviewing each one of the case studies individually in Chapters 3-5, there will be a substantial amount of data for carrying out a robust and consistent investigation on Taguchi tools for experimentation. Thus, Chapter 6 will investigate the integration of Taguchi and non-Taguchi tools and the effect they have on location and dispersion control. This chapter will make use of special experiment designs (involving full factorial arrays) for studying the interoperability of these tools, which will allow for a fair comparison between them. Outcomes from this study (Fig. 1.2) will be directed towards suggesting guidelines for a better use of these tools to get the most out of Taguchi methods.

Chapter	Case / *Objective*	Main array	Taguchi arrays	SN ratios	Controllable factors	Noise factors
3, 6	Milling / *Surface finish*	Full factorial	L_{16}	STB	Tool speed Workpiece speed Coolant use Direction of cut Depth of cut Number of cuts Tool type	
4, 6	Traffic Flow / *Delay*	Full factorial	L_{32}	STB	Controller Type	Speed distribution Vehicle mix Profile slopes (3 branches) Profile magnitudes (3 branches)
5, 6	Genetic Algorithms / *Parameter optimisation*	Full factorial	L_{16}	LTB	Crossover probability Mutation probability Number of generations Population size Tournament size	

Table 1.1 Summary of design settings for the three case studies.

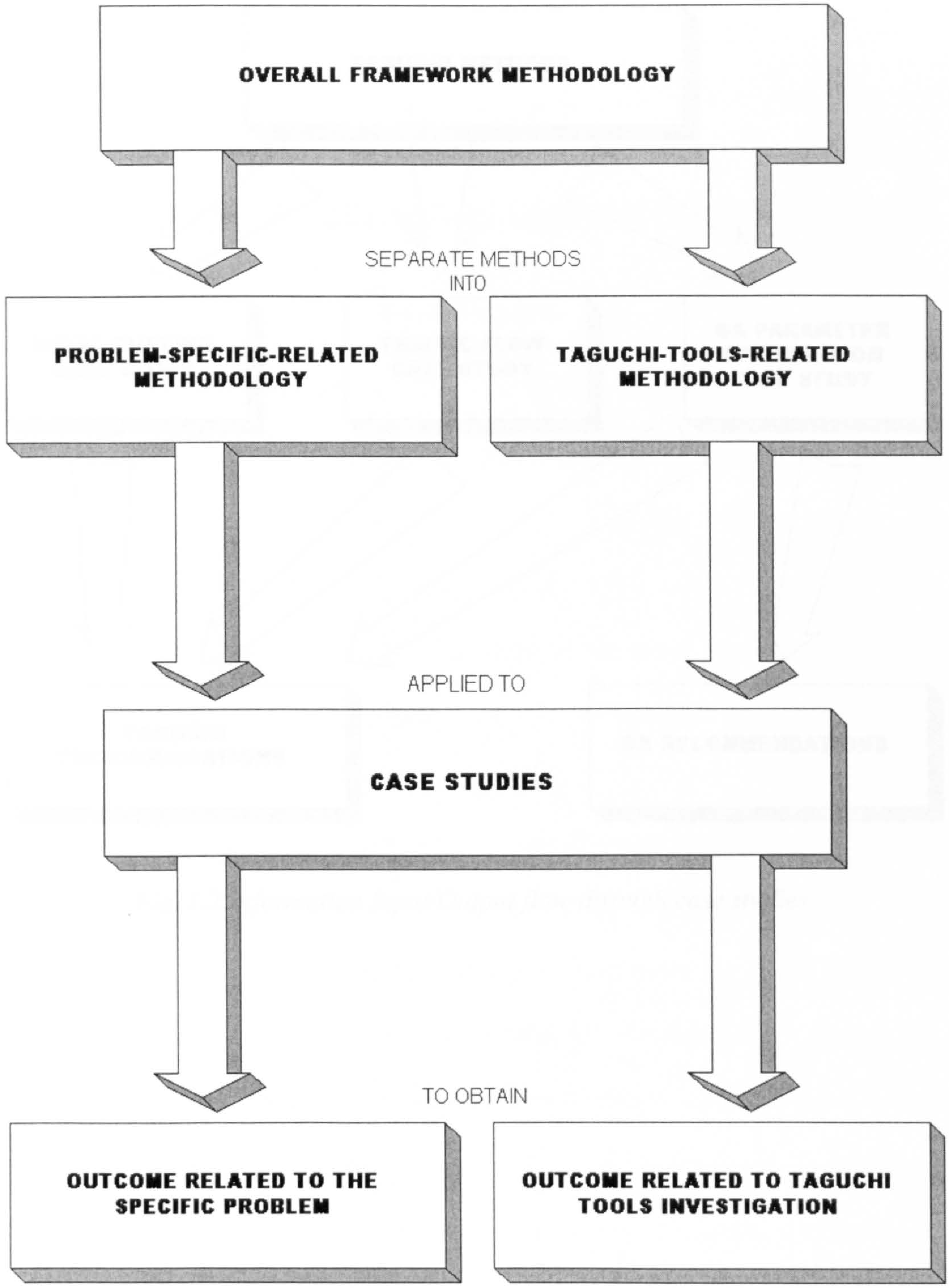


Fig. 1.1 Overall experimentation strategy.

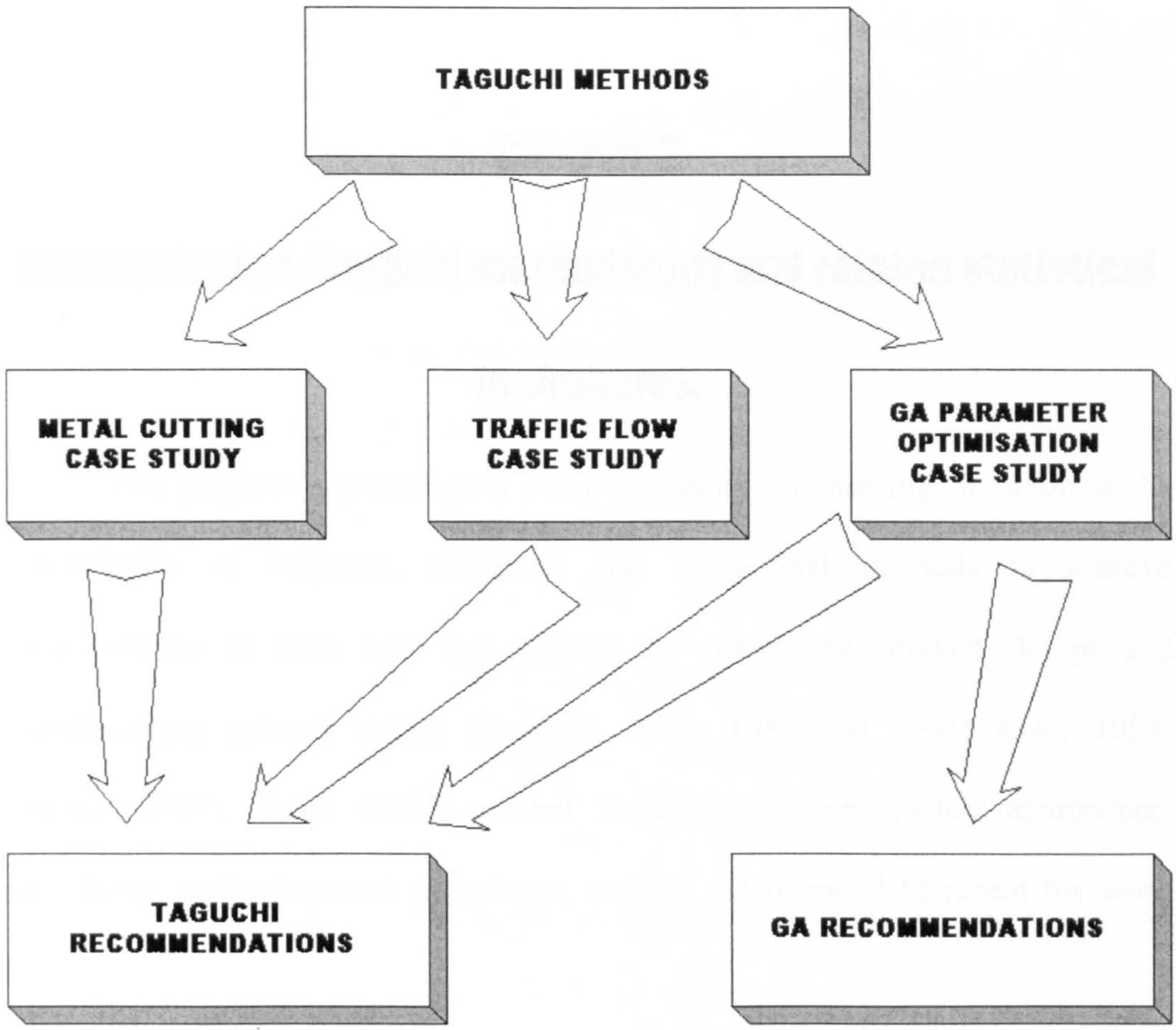


Fig. 1.2 Information Input/Output flow through case studies.

Chapter 2

Robust design, Taguchi methodology and related statistical techniques.

The Taguchi approach is a form of quality engineering. It involves the combination of technical, statistical and operational methods to achieve improvements in both cost and quality, by optimising product design and manufacturing process design (Taguchi, 1986, 1987 and 1993; Ross, 1988; Condra, 1995). Taher (1995) related Taguchi to other quality approaches, identifying similarities and differences, so it is not intended to repeat his work here.

Faster responses to changes in global market forces require the implementation of positive-improvement cycles (eg Fig. 2.1). However, such improvement cycles require acceptance and support from all levels inside the organisation, and simple methodologies are more likely to achieve this. Within this framework Western industry has responded to Taguchi's message since he has transformed what might appear to be a somewhat abstruse academic discipline into a practical business management operational methodology (Condra, 1995). He has linked it directly to the improvement of business performance and delivered a complete package that industry can run. The real message of Taguchi, and his greatest contribution, does not lie in the development of novel statistical methodologies, but in how to package and market statistical methods to capture the interest of the non-statistician and to generate sufficient enthusiasm and commitment to ensure its success in industry (Barker, 1990).

Modern product designs and manufacturing conditions are nearly always complex. Numerous factors are involved and it is the job of the engineer to know the process and to provide specifications for operating machines that allow the optimum manufacture of a product. In practice, a significant part of these specifications may have to be determined empirically. Unfortunately, unless experiments are done in a planned manner, the results may be neither repeatable nor may they improve the process or product. Planning experiments is a topic that has been around for many years (Mead, 1988; Fisher, 1966; Mason, 1989). Classical Design of Experiments (DoE) methods (Montgomery, 1991), created and developed by statisticians, have been the standard for generally accepted experimentation techniques available to date. However, the complexity of products nowadays, as well as of the manufacturing processes required to make them, forces experimenters to think carefully whether to choose classical methods (which offer designs frequently expensive and difficult to perform) instead of apparently simpler and cheaper alternative methods (such as Taguchi methods). As a result, there is a extensive literature criticising or debating the Taguchi approach (Gunter, 1987; Box, 1988; Box *et al,* 1988; Adams and Woodall, 1989; Denhad, 1989; Logothetis and Wynn, 1989; Bullington *et al,* 1990; Chan and Ho, 1990; Lochner and Matar, 1990; Wu *et al,* 1990; Lyon *et al,* 1991; Kackar, 1985; Myers *et al,* 1992; Nelder, 1992; Welch *et al,* 1992; Wu, 1992; Peace, 1993; Robinson, 1993;

Fowlkes and Creveling, 1995; Rowlands, 1995) or seeking to provide advice on its application (Kackar, 1985; Box, 1988; Kackar and Tsui, 1990; Taher, 1995).

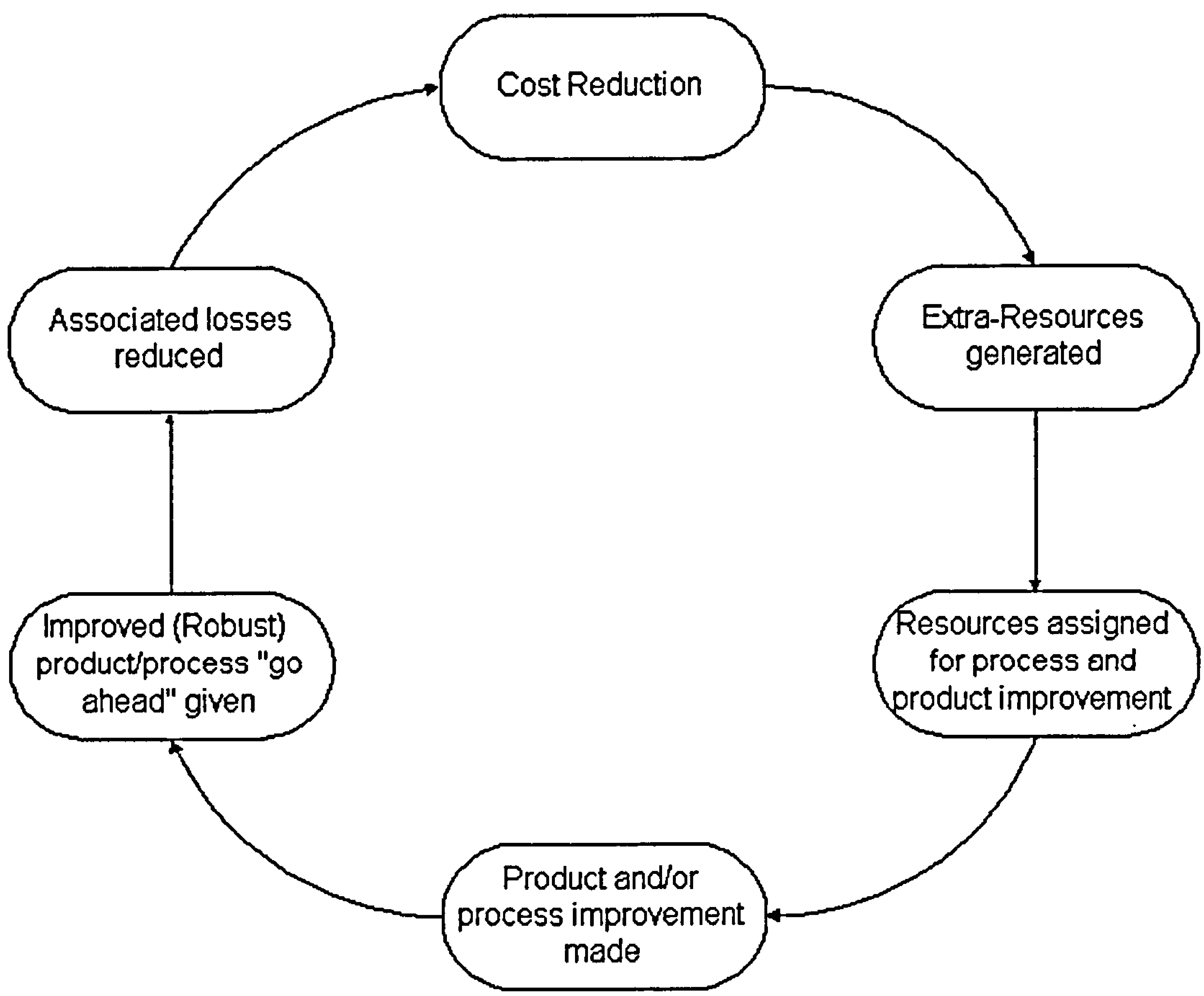


Fig. 2.1 Positive-improvement cycles (Garzon, 1995)

2.1 Robust Design

The Taguchi philosophy for robust design has been acclaimed since it was first applied by Japanese manufacturing companies, and later by Western manufacturers (Ealy 1988). Obviously, the success of Japanese manufacturers did not rely only on one single set of methodologies or techniques. Developments of new products with high levels of performance are a fascination for Japanese workers and managers, levels that can be attributed to many engineering and management techniques, including Taguchi Methods. Clarke (1997) and others (Ross, 1988; Peace, 1993; Barker, 1990; Fowlkes and Creveling, 1995; Lochner and Matar, 1990) outline some of the basic concepts behind the Taguchi approach. As in other philosophies (Taher, 1995), Taguchi suggests an overall environment to achieve a quality target. This environment should aim to achieve controlled production of products with superior quality and is called an *overall quality system* (Taguchi *et al*, 1993; Fowlkes and Creveling, 1995). Ideally, this is an integrated system of overall quality control in which all activities interact to produce products with minimum deviations from target values that will minimise quality costs and make the most economic use of human and other company resources (Ross, 1988; Taher, 1995).

The overall system involves the quality concept and quality cost through all phases of the product life cycle (Condra, 1995). The life cycle begins with market development and product planning and continues through the phases of product design, production process design, on-line production process control, and packaging, as well as maintenance and product service after purchase (Clausing, 1994). All these activities must be improved in order to obtain good quality and productivity standards. However, in order to achieve *robustness*, Taguchi identified that quality control efforts must begin in the product design phase and not just be applied through the production engineering and production operation phases (Taguchi *et al*, 1993). Taher (1995) has compared Taguchi's with other concepts of robustness.

The broad purpose of the overall quality system is to produce a product that is *robust* with respect to all "noise" factors. Robustness, which is one of the important concepts applied to quality by Taguchi, implies that the product's functional characteristics are not sensitive to variations caused by noise factors (Peace, 1993). Noise factors are uncontrollable sources of undesirable variation in products during manufacture or subsequent operations. The aim of *robust design* is to reduce the impact of noise factors on the quality of a product by work done at the design phase (Taguchi, 1987). Not all variation can be eliminated, but the sensitivity of the system to sources of variation can often be altered so that they become less important to overall performance. Robust design is concerned with how to reduce the variations in product performance. Taguchi formulated many of the basic ideas behind robust design in the 1950s (Ross, 1988). It uses many ideas from statistical experimental design and ANOVA to obtain dependable information about variables in making engineering decisions (Fowlkes and Creveling, 1995). Design must take account of variability in manufacture so design principles can be applied to identify design and process settings that minimise variation in manufacture and minimise the effect of those variations on product performance once it is in the customers' hands (Bendell, 1988; Lochner and Matar, 1990).

Robust product and process designs can be achieved through Taguchi's approach to Quality Engineering. Quality Engineering involves both Off-line

Quality Control (product and process design) and On-line Quality Control (process monitoring and control) activities (Ross, 1988). Off-line Quality Control activities, which involve both product design and process design, are in essence an engineering optimisation method for products and/or processes. According to Taguchi, they consist of three steps: system design, parameter design and tolerance design (Taguchi, 1987).

"System design" is close to conventional views of engineering design. It involves innovation and requires knowledge from science and engineering fields. The main objective of system design is to determine the manufacturing processes that can produce the product within the specified limits and tolerances at the lowest cost (Peace, 1993).

"Parameter design" is the key stage of Taguchi's methodology (Bendell, 1988). Parameter design selects levels or values of controllable factors that are design parameters to minimise the effect of noise factors on the functional characteristics of the product. Parameter design in production process design determines the operating levels of the manufacturing process factors so that variation in product parameters is minimised (Ross, 1988). This is the key step for achieving high quality without an increase in cost. Its strategy is to recognise control factors and noise factors and to treat them separately.

Finally, “tolerance design” is employed only if the reduced variation obtained through parameter design is not sufficient. Tolerance design involves tightening tolerances on product parameters or process factors whose variations impart a large influence on the output variation (Ross, 1988; Peace, 1993). In other words, tolerance design typically means spending money in terms of better resources (better-grade materials, components or machinery) and in Taguchi's view should be avoided through careful parameter design.

Taguchi's three-stage approach for quality improvement activities can also be applied without using physical experiments but through simulations. In some cases, it may be cheaper to create and run simulation environments for product and process improvement. Parameter Design would be appropriate for attempting to optimise or improve performance through the simulation model by carefully selecting settings for some of the decision factors in the model.

2.2 Taguchi Methods

Taguchi, like Deming and others (Taher, 1995), has both a philosophy and a methodology. It is important to distinguish between Taguchi's quality engineering approach (the philosophy described above) and his methodology (statistical experimentation) though there is no definitive statement of exactly what constitutes Taguchi Methods (philosophy and methodology). This distinction takes up more importance since Taguchi's quality engineering philosophy has received wide acclaim, whereas some of his methodologies have been criticised (Kackar, 1985; Logothetis and Wynn, 1989; Barker, 1990; Condra, 1995; Taher, 1995).

Robinson (1993) pointed out that Taguchi's packaging of his methodology is usually presented as having three important components (orthogonal arrays, linear graphs and interaction tables), which makes it appear easier to use than other standard alternatives (for instance, Box *et al*, 1978). But there are other concepts, not so straightforward as those three elements, which play an important role in this methodology. Taguchi introduced the idea of targeting simultaneous cost reduction and quality improvement through reduction in variation (Ross, 1988). He also suggested a structure to distinguish between factors which are controllable and those which are not (noise factors), as well as dealing with the values of controllable factors to minimise the effect of noise factors on the response(s). Other innovations, such as the inner array for control factors and the outer array for noise factors, have been more controversial (Gunter, 1987; Taher, 1995). However, Taguchi's most innovative (though controversial) concept is his response joint-modelling metric called Signal-to-Noise ratio (SNR). SNR attempts to model both location and dispersion effects in a single metric for easier visualization and understanding. This approach looks practical but its statistical background seems biased, which is the core of the controversy. Many authors (Box, 1988; Logothetis and Wynn, 1989; Myers *et al*, 1992; Nelder, 1992; Taher, 1995; Rowlands, 1995) have pointed out deficiencies in the SNR concept that may make it non-viable until a more reliable, single-metric replacement is suggested. All these aspects are combined and consolidated in a package (Taguchi tools) which consists of three groups of novel concepts (Table 2.1).

Additionally, Taguchi offers tools for attribute data (eg product attributes that cannot be measured or quantified), such as Accumulation Analysis, and for on-line quality control activities. The positive aspects and drawbacks of accumulation analysis can be found in the literature (Hamada and Wu, 1990; Nair, 1986; Box and Jones, 1986; Yanagisawa *et al*, 1990), as well as extensive documentation regarding Taguchi's online quality methods (Taguchi, 1987;

Fowlkes and Creveling, 1995; Peace, 1993; Taguchi *et al*, 1993). However, despite the interest and controversy surrounding these techniques and the advantages they may offer, they are not in the scope of this study.

Group	Tools	
Quality engineering concepts (Sections 2.2.1 to 2.2.3)	Loss function to quantify quality performance in terms of cost	Signal to Noise ratios as quality metrics where both target performance and its variation are to be optimised.
Statistical DoE methods (Section 2.4)	Pre-defined fractional factorial arrays for experiments.	Special assignment techniques for factors in experimental plans.
	Treating interactions as noise to secure performance robust to interactions	Linear graphs to determine interactions
Methods of analysis (Section 2.4)	The use of "outer" experimental arrays to investigate noise effects.	The conduction of a confirmatory experiment.

Table 2.1 Principal Taguchi Tools

2.2.1 Loss to society - Taguchi's Loss Function and Signal to Noise Ratios.

Fundamental to Taguchi's approach to quality engineering is the concept of loss. Taguchi based his philosophy on a societal view of quality (Taguchi *et al*, 1993). His proposed aim of quality control is to reduce the total societal cost by implementing innovative techniques which produce savings to society (this was a new way to think about investments in quality improvement projects). Taguchi associates a loss to society with every product that reaches the consumer's hands. This loss includes, among other things, consumer dissatisfaction, added warranty costs to the producer and loss due to a company having a bad reputation, which leads to eventual loss of market share (Ranjit, 1990). The total loss generated by a product to society is an important dimension of the quality of a manufactured product (Kackar, 1985; Kackar and Shoemaker, 1986).

In fact, the idea of minimising loss to society is rather abstract and thus difficult to deal with as a company objective. Usually, quality costs are quantified in terms of scrap and rework, warranty, etc. However, other items (such as hidden costs or long-term losses related to engineering/management time, inventory, customer dissatisfaction and losing market share in the long run) are commonly ignored but can be related in some way to the concept of loss within a company context (Fig. 2.2), which may be visualised as the combination of three types of loss: Loss to the Manufacturer, Loss to the Customer and Loss to Society. Loss in any case starts with the manufacturer (Group A – Fig. 2.2) whose different types of loss (ie 1 to 5 – Fig. 2.2) induce losses to the customer (Group B – Fig. 2.2). Customers and Manufacturers belong to society and as a consequence their loss would have an impact on Society (Group C – Fig. 2.2). So, how do they link? There may be three clear paths linking those three groups. The first path (1, 6 and 10 – Fig. 2.2) suggests that those causes attributable to the actual manufacturing processes (ie inspection, rework, resources used in unusable products, etc.), which are losses to the manufacturer, would cause loss to the customer through service and warranty costs (higher production costs due to rework would also translate into higher retail price, going directly to the customer). Once those products cease to function for the customer and service costs are too high, the product would be disposed of causing a loss to society by polluting the environment. Similarly, waste coming from the manufacturer would have an impact on the environment causing extra loss to society. The second path (2, 3, 7, 8 and 11 – Fig. 2.2) refers to the loss caused to the manufacturer by shipping defective products (through warranty, returns and recall costs), which at the same time causes losses to customers due to malfunctioning products. Customers may face two types of costs due to malfunctioning products: cost to replace damaged (or being repaired) products and loss of profits associated with these. Society becomes affected as there is a disruption in customer activities in the meantime, which depending on the product and the customer may mean more serious disruptions (for instance, if the product is a spare part for an aircraft, and the customer is an airline, society is affected by schedule alterations, cancellations and/or delays). Finally, the third path (4, 5, 9 and 12 – Fig. 2.2) goes a step further within the manufacturer. If products significantly deviate from target specifications (Taguchi, 1993), there is a loss for the manufacturer due to bad reputation among customers. Customers are affected because they may spend time and effort on working around those product glitches. Depending on the approach taken (the risk and difficulty of such work-arounds), they may cause personal injury or death, causing a loss to society. This personal injury or death may translate into loss to the manufacturer through lawsuits. Lawsuits may also come from unsatisfied customers, depending on the products' terms and conditions.

This corporate view of loss may be an approach to satisfy, in some way, the claims of Kackar (1985) that Taguchi's definition of loss to society is incomplete. This view tries to adjust and extend Taguchi's definition of loss beyond conventional definitions and include societal losses during manufacturing. From this viewpoint, loss to society can be considered a consequence of more conventional views of loss. The reduction of variation improves quality by having more product consistency, resulting in lower costs of rework for the manufacturer or repair/loss for the customer. Taguchi suggests that once loss to producer and/or customer is reduced, the Loss-to-Society will also be minimised (Taguchi *et al*, 1993).

Taguchi's concept of Loss-to-Society is, in fact, relating quality to monetary loss and not to other factors or conditions (Ross, 1988). Even though the actual loss may be the loss of functionality to the product, or other losses such as pollution, time, noise, etc., the overall effect is a financial loss. The conventional method of computing the cost of quality is based on the number of parts rejected and reworked. This method of quality evaluation is incapable of distinguishing between two samples, that are both within the specification limits, but with different properties (Fowlkes and Creveling, 1995). According to Taguchi (1987), performance begins to gradually deteriorate as the design parameter deviates from its optimum, ideal or target value. A distinction should be made here between measuring loss only outside the tolerance limits (Fig. 2.3(a)) or as Taguchi does for any deviation from target (Fig. 2.3(b)). Taguchi (1987) proposed his Loss Function, to measure the deviation from the ideal value and to quantify these losses in monetary terms. This Loss Function takes the following basic (continuous) quadratic form:

$$L(x) = k \bullet (x-m)^2 \qquad (2.1)$$

where L is the loss in monetary terms (eg pounds, dollars), m is the point at which the characteristics should be set, x is where the characteristic actually is set, and k is a constant that depends on the magnitude of the characteristic and the monetary unit involved (Peace, 1993).

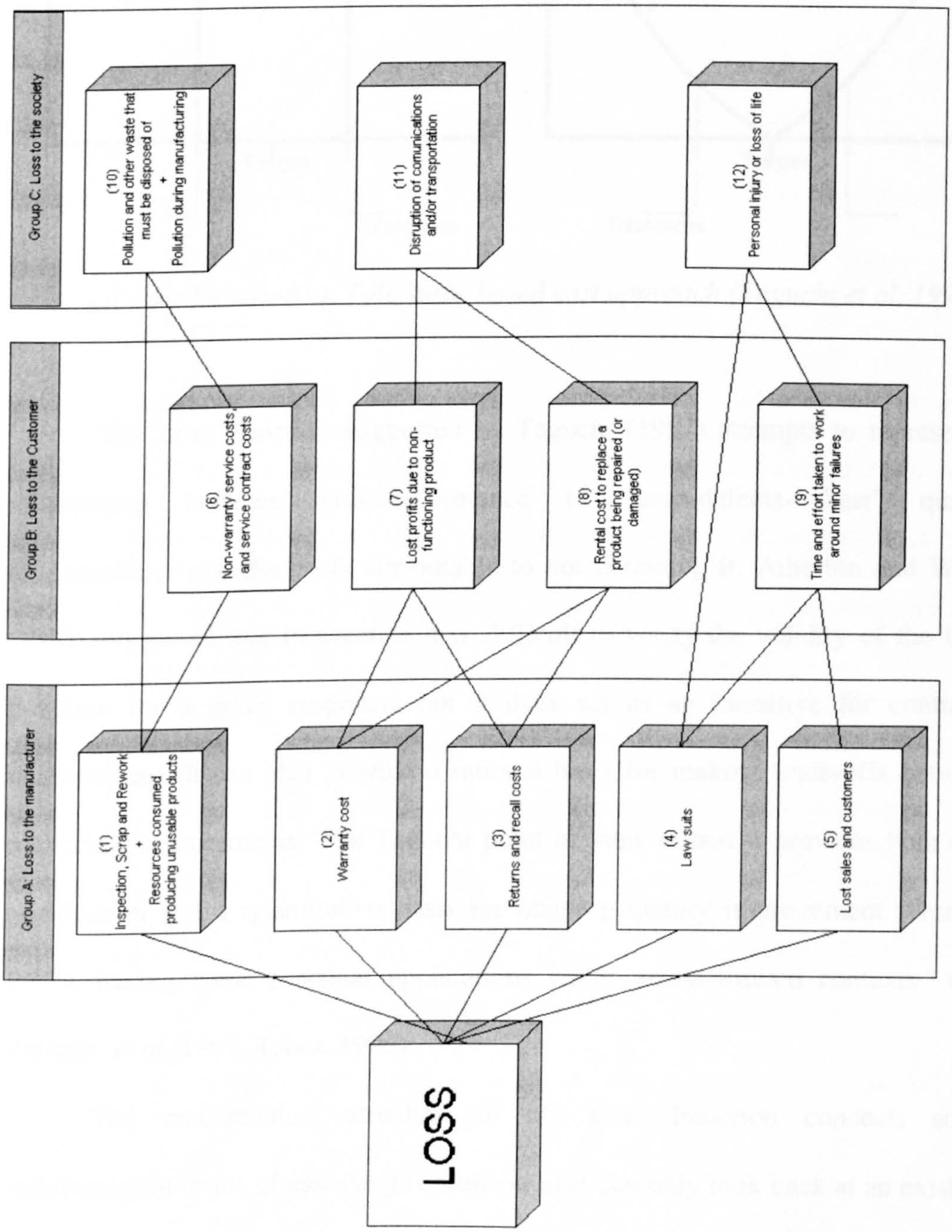


Fig. 2.2 Taguchi's Loss concept from a corporate/company view.

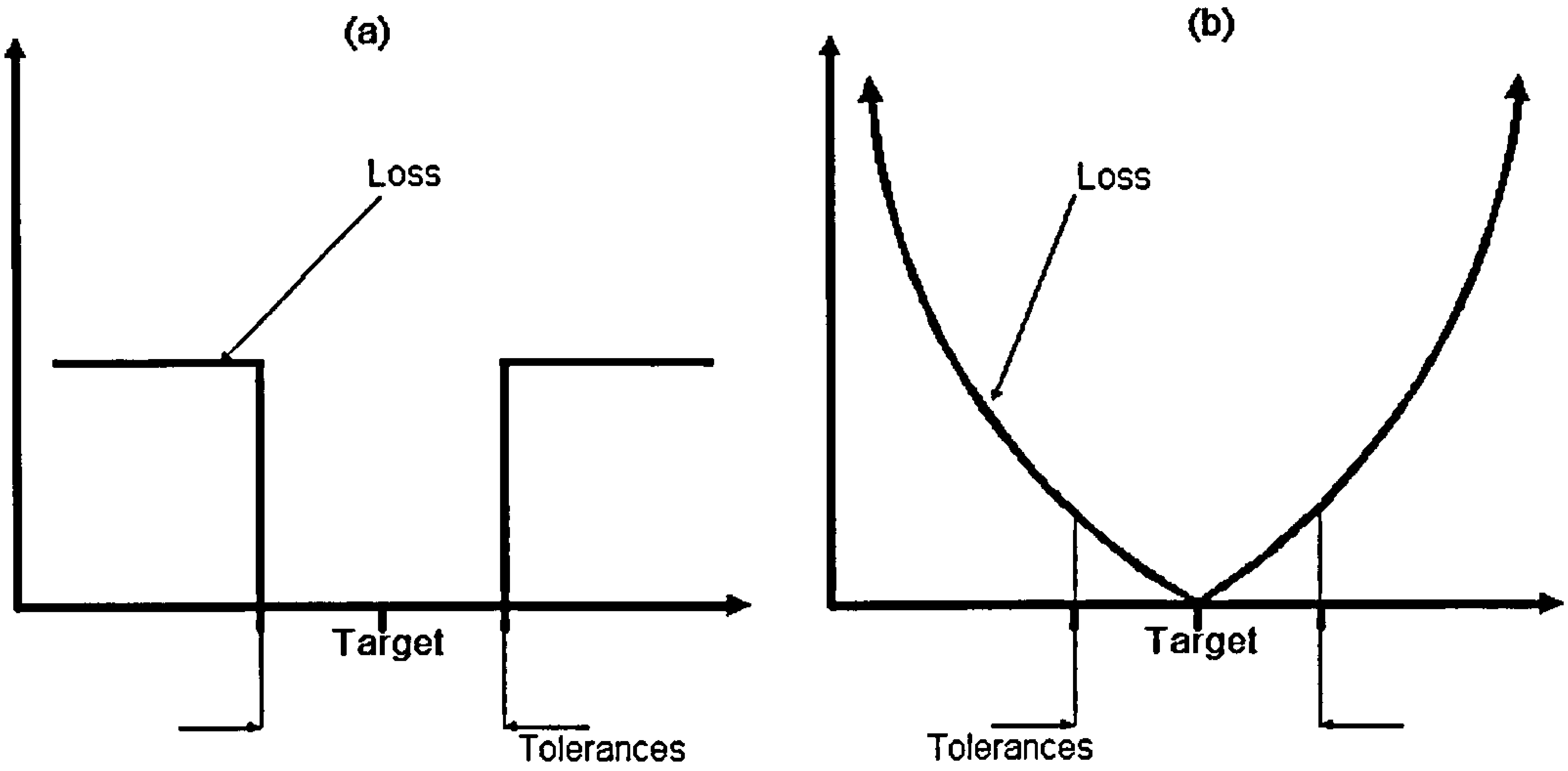


Fig. 2.3 Loss Function vs. Tolerance-based cost approach (Taguchi et al, 1993).

The Loss Function suggested by Taguchi (1987) attempts to represent a relationship between non-conformance to "zero-defects-is-best" quality characteristics and the costs attributable to not obtaining it. Atherton and Wynn (1993) suggested that in practice it is difficult to verify the validity of the Loss Function for a given response, but it does act as an incentive for continual improvement. It can also provide a rational basis for making trade-offs between conflicting requirements. The Taguchi point of view is that it provides both cost justification and a quantitative basis for ongoing quality improvement (Gunter, 1987), having some practical applications within some limited contexts (see Vasseur *et al*, 1997; Taher, 1995).

The mathematical structure of the Loss Function conceals some deficiencies in terms of assessing robustness as it can only look back at an existing performance and quantify it (Barker, 1990). More importantly, the Loss Function is not suitable for optimising parameter design as it is unable to reduce dispersion independently of location (Fowlkes and Creveling, 1995). With these in mind, Taguchi (1987) proposed a more performance oriented metric, SNR, which is intended to combine both location and dispersion measures. The mathematical expression for SNR is a derivation of a form of Loss Function and is developed from it (Taher, 1995). Kackar (1985) and Leon *et al* (1987) have shown how SNR is related to the Loss Function. The SNR is intended to reflect the variability in the response of a system caused by noise factors (Ross, 1988). Taguchi's approach to data analysis begins by defining SNR as a summarising quantity, and then seeking a model for it in terms of the experimental factors (Bendell *et al*, 1990). SNR, which is related to the choice of Loss Function (Parr, 1988), seems to be Taguchi's way to put the Loss Function up front to determine factor significance. By implication the SNR response requires that at least two observations/repetitions (Section 2.3.2) should be done for a single experimental replication since it would be necessary to determine a value of standard deviation (SAS Institute, 1991).

Although it is attractive to some experimenters that the use of standard SNR avoids the necessity of thinking about their experiment, avoidance of thought, as usual, does not pay in the long run. Box (1986) and Pignatiello and Ramberg (1985) suggested that it is better to study the mean and the variance separately rather than combine them into SNR as Taguchi suggests and the evidence from Taher's study (1995) supports this view. Box (1988) suggested the use of data transformations as a better alternative to SNR (Section 2.3.1). Nelder (1992) proposed Generalised Linear Models (GLM) as another alternative to SNR. He recommends GLM because they allow the behaviour of the mean and variance to be modelled quite separately, reducing the risk of correlation (as well as other properties) between the estimator and location and dispersion measures. Furthermore, when a GLM is used the data is not transformed, so its original dimensions are preserved throughout. Vining and Myers (1990) suggested the dual response approach, estimation of the mean and variance separately for each point of the inner array, to overcome many of the difficulties in using the SNR. This method also introduces more complicated models for estimating the response moving from ANOVA to regression techniques. They use linear regression models for estimating the mean and variance. Nelder (1992) extended this idea by using GLM to simultaneously model the mean and variance. The strategy remains the same in all these approaches, to identify location and dispersion factors, minimise variability and adjust to target.

2.2.2 Taguchi and Design of Experiments.

Traditionally, engineers used to improve a product adjusting one parameter at a time, but the effectiveness of this is often overshadowed by far more efficient ways of experimentation, such as Design of Experiments (DoE) (Clarke, 1997). DoE is a methodology for systematically applying statistics to experimentation (Box, 1988). This methodology compromises nothing in thoroughness but is, generally, less time-consuming than “one factor at a time” methods, being applicable to both laboratory research and manufacturing processes. Although DoE is a very useful tool, it has been underused in the U.S. and, according to software vendors' estimates, fewer than 5% of U.S. engineers and scientists have any formal training in DoE (Hockman and Berengut, 1995).

Designing an experiment is controlling and changing systematically the values or settings for the various factors, as well as measuring and analysing the effects of these changes on the responses. Therefore, the decision on which design to use is based on particular objectives. Hockman and Berengut (1995) classified design types into three groups: Screening, Interaction (or Factorial) and Response Surface Designs. This seems a more practical and simpler (for engineers) classification of design types than that suggested by Montgomery (1991) and Box *et al* (1978) which classifies fractional factorial designs according to their resolutions (III, IV and V). Screening designs are commonly used to decide which of a system's many variables are significant ones. They provide only a limited amount of information regarding variables in the system, but they require the fewest number of runs for a given number of variables (Bechhofer *et al*, 1995). Interaction designs, also known as factorial designs, help experimenters to understand how variables interact to influence responses. These designs include runs for all experimental settings, though they look at fewer variables than screening ones do (Montgomery, 1991). Interaction designs assume that values for input variables affect responses linearly. Response surface designs are useful in those situations where curvature effects are required. These are similar to full factorial designs in their capability to determine factor effects and interaction effects for a small number of variables and need more experimental runs than do interaction designs (because they require at least three levels to estimate curvature)

(Montgomery, 1991). These designs permit researchers to define empirical models (usually quadratic polynomials) that describe how responses behave at all values or settings of the variables in the experimental region (Hockman and Berengut, 1995).

It should not be difficult to assume from this classification that factorial designs have a wide range of applicability as they could perform well as either screening or possibly response surface designs (Taher, 1995). Certainly, factorial experiments extract information on several design factors more efficiently than could be done by the traditional one-factor-at-a-time test (Mead, 1988). Their main objective is to determine the effect of various factors on some characteristics of a product (Grove and Davis, 1992). In some situations these experiments can be costly and time consuming and it is not practical to plan an entire full-factorial experimental program. Testing every combination of variables is impossible in a manufacturing environment, because problems tend to be complex and time is usually in short supply. Instead, a fractional factorial experiment is run. This requires testing only a fraction of the total number of possible test combinations. This "fraction" is the representative test combination carefully selected from the total test combinations (Hicks, 1973). Fractional factorial experiments obviously cannot produce as much information as the full factorial. However, economy is obtained at the expense of assuming that some of the interactions between factors might not have great influence on the response (Montgomery, 1991; Plackett and Burman, 1946). One way of promoting the use of fractional factorial experiments is to package the necessary statistical know-how in a form that makes it easy for the experimenters to plan these experiments on their own (Kackar and Tsui, 1990). That is what Taguchi does, offering a simple methodology for planning/designing an experiment.

Taguchi considers that conventional experimental design techniques were developed for use in scientific research for the determination of Cause-Effect relationships (Peace 1993). However, in many cases, even knowing the cause cannot solve the problem because the removal of the cause is too costly. In such cases, efforts can be made not to eliminate the cause but to find countermeasures to reduce the cause's influence. Such cost-effective attitudes are the basis of the differences between Taguchi's quality techniques and conventional experimental design techniques (Table 2.2).

For complex problems, the number of variables soon takes the theoretical number of experiments, even in fractional factorial experiment designs, into fantasy territory. There are ways around this problem. Taguchi believes that, for many products, there is a wealth of engineering experience which knows whether a particular factor is likely to be important or not in terms of performance, though Taher's (1995) case studies showed that even where there is an extensive literature this rarely discusses variation or its causes. Prior knowledge can in principle be used to cut the number of factors down, but it is the unknown things that really matter. Resorting to other methods, such as simulation environments, may assist practitioners in determining the right choice for combinations of factors and suitable experimental designs for a desired performance. For instance, Newton et al (1987) have developed an expert system for experimental-design techniques that automates the selection of an orthogonal array and the design of an experiment. The Prolog-based program uses artificial intelligence to assist practitioners in the design of complex experimentation.

A key aspect of conventional Design of Experiments, that is the consideration, study, and estimation of interactions, is overshadowed in Taguchi's view by the fact that the existence of interactions complicates research efficiency since all combinations of variables must be investigated in order to obtain the necessary information. As the Taguchi methodology aims to make a process or product less sensitive to variations without adding cost to the product (Ross 1988), the justification given for Taguchi's philosophy on interactions is that the design engineer needs to determine, through laboratory experiments, settings of control factors that are optimal in the manufacturing conditions and in the customer's use conditions (Taguchi, 1987). Taguchi (1987) believes that significant interactions of order higher than two are extremely rare in practical design and manufacturing problems and that any important interactions will occur only between the most significant controllable factors. His recommended fractional factorial experimental arrays are based on these premises. As long as it is not possible to assume minimised interactions between control factors, it is impossible to render an efficient experiment. Some countermeasures to avoid the consequences of ignoring interactions are the use of Data Transformation, accumulation analysis, assignment of interactions (Linear Graphs) and distribution of interactions (Pignatiello and Ramberg, 1985; Sullivan, 1987; Taguchi, 1987; Wu and Chen, 1992).

Graphical analyses have become accepted as powerful tools for many kinds of statistical problems, with some of them working, instead, as design aids. Linear Graphs are one of them. Linear Graphs add flexibility to orthogonal arrays (Peace, 1993), to minimise the effect of confounding. A way of avoiding the consequences of ignoring interaction effects is assigning them to orthogonal arrays together with main effects. In this way it is supposed that interactions could be neglected without having direct effect on the main factors. Linear graphs simplify this process. Linear graphs can be reinforced with the use of orthogonal arrays in which interaction effects are distributed evenly throughout the array (Taguchi and Konishi, 1987; Barker, 1990; Fowlkes and Creveling, 1995). This method is widely used with Taguchi arrays as a way to reduce confounding effects. One of its limitations is that it presupposes that the experimenter has prior knowledge of the significant interactions so as to use linear graphs to suggest where factors should be allocated. Linear graphs make it easier for non-statisticians than going through the algebra of aliasing relations (interactions table). However, Linear Graphs should be used with discretion. As shown by Wu and Chen (1992), for larger problems Taguchi's method (linear graphs) is deficient.

Other approaches to experimentation, such as Sequential Experimentation, proposed by Vining and Myers (1990), Hockman and Berengut (1995) and Taher (1995), are recommended not only to optimise the operational use of DoE but as a strategy for problem solving and cause's influence reduction/removal. Hockman and Berengut (1995) suggested the sequential approach should start with a screening experiment only whenever researchers do not know precisely which variables are significant from the beginning. Then, after a screening experiment has reduced the number of variables, a standard Plackett-Burman design (Plackett and Burman, 1946) may be ideal for the reduction of the experiment size, followed by a response surface design for a face-centred-cube (Vining and Myers, 1990). With this, a model to determine how the system of variables and responses would behave has been created. There are many types of designs, so Plackett-Burman (1946) designs can be replaced, for instance, by other fractional factorial designs or Taguchi designs (which are modifications of Plackett-Burman's). Taguchi methods were custom-designed for engineers, and an important ingredient of their success or otherwise is the special knowledge an engineer should have of a product or process (Taguchi *et al*, 1993). This knowledge is what makes it possible to shortcut traditional test-every-combination experiments but this restriction placed by Taguchi on his methodology is often overlooked in practice.

Finally, Taguchi attaches great importance to confirmation experiments in his design strategy - that is a small follow-up experiment to confirm the findings from analysis of experimental data (Ross, 1988). This reflects the possibility with highly fractionated designs that the optimal combination found by analysis may not have been included in the original design array. A distinction should be made between traditional Response Surface Methodology, which commits more runs to regression model building, and this approach, which commits more runs directly to confirm results.

Tool	Taguchi Method	Standard method
1	SN ratios	Appropriate transformations; separate analysis of means and (log) standard deviation
2	Orthogonal arrays	Screening, factorial and fractional designs
3	Linear Graphs	Aliasing procedures and tables
4	Inner and Outer arrays	Sensitivity analysis; variance component analysis; nested and split plots designs
5	One-shot designs; confirmation/optimisation runs	Sequential design strategy; response surface methods; computer methods
6	Two-stage procedure using signal and noise variables	Analyse location and spread separately; importance of interactions; residual analysis
7	ANOVA for analysis	Normal probability plotting; other graphical techniques; standard regression techniques
8	Outliers not considered in analysis	Residual plots and/or resistant data analysis procedures

Table 2.2 Comparison of Taguchi methods with standard statistical design and analysis methods (Gunter, 1987).

2.3 Complementary analysis tools/techniques

There are conventional statistical techniques to address most of the common issues (such as experimental bias/error, variation, correlation, modelling) found in experimentation (Table 2.2) which have been applied within the DoE context (Daniel, 1976). Some of these techniques can also be applied with Taguchi methods to overcome some of their deficiencies and to make their implementation more robust. Specifically, the use of Transformations (tipped by Box (1988) to be a better replacement for SNR), repetitions, randomisation, robust statistics and the Response Surface Methodologies (RSM) (Sections 2.3.1 to 2.3.4) will be reviewed here.

The aim of diagnostics in regression analysis is to provide information on the appropriateness of the assumptions made in fitting a regression model to data. Data with nonconstant variance can be analysed in two different ways; one is to transform the response variable, and the other is to fit the data using a weighted regression model (Montgomery and Elizabeth, 1992). It should not be surprising that for some data sets the transformation that induces normality will not stabilise the variance. Thus Carroll and Ruppert (1988) proposed a model combining both transformation and weighting.

2.3.1 Transformations

The use of data transformations has been suggested as a better alternative to Taguchi's SNR (Box 1988). This method seeks a transformation of the data, $F(y)$ in place of y, with the aim of fulfilling two criteria, separation and parsimony. Separation means that the transformation should eliminate any unnecessary complication in the model due to functional dependence between variance and mean, and parsimony means that the transformation should provide simple additive models for the mean and dispersion (Andrews, 1971).

Many nonstandard problems are best addressed by transforming the data to achieve increased linear association. The use of transformations has been proven to be very successful for reduction of interaction effects in designed experiments (Hoyle, 1973). However, there exists always the doubt of what transformation to use. There are many types of transformations that have been proven to be statistically robust and consistent. Most of these rely on complex statistical procedures to determine the most appropriate transformation. Sometimes those procedures can be irritating and cumbersome for experimenters with little statistical background. The transformation range goes from simple power and logarithmic expressions, passing through derivatives, to the most widely used: the Box-Cox method (Sakia, 1992). De Veaux and Steele (1989) suggest a very interesting approach, the Alternating Conditional Expectation (ACE) algorithm, to suggest reexpressions, after analysing the pros and cons of different suitable methods. But, unfortunately, that method is awkward due to the length and complexity of the different steps. At the same time, they also suggest the Box-Cox method as an alternative approach.

The Box-Cox method (Box and Cox, 1964) has been widely used since it was first proposed because of its simplicity and robustness (Sakia, 1992). It has inspired a large amount of research on its applicability, including applications with Taguchi Methods (Fearn, 1992; Taher, 1995) as well as on the drawbacks arising from its use (Sakia, 1992). Nowadays, statistical software often bases its transformation modules on Box-Cox methods (e.g. the SAS package (SAS Institute, 1996) finds optimal transformations through the Box-Cox method). Obviously, that is not the only available method and there are other options like special transformations which are recommended for particular situations. For instance, the Omega transformation can be used to improve the additivity of characteristics such as percent defective (Taguchi, 1987). Taguchi (1987) proposes the Omega transformation for responses such as percent defectives or yields that do not have good additivity, particularly in the region around 0% or 100%. Taguchi recommended this transformation for being used as part of a *recipe* for analysing ordered categorical data (to combine with accumulation analysis to identify important factors and estimate/predict performance at the new settings).

2.3.2 Randomisation and repetitions

In using DoE, researchers need to be certain the estimated factor effects, interaction effects and curvature effects are real. Otherwise, the model prediction about the experimental process would be inaccurate or misleading. To gauge the reality of effects, all experiment designs include techniques for understanding and mitigating the effects of the two basic types of experimental error: bias error and random error (Hockman and Berengut, 1995). Experiment designs control bias error by manipulating the order of the experimental runs via two statistical methods called randomisation and blocking (Ross, 1988). The impact of random error is minimised by replications (repeating runs statistically) and by averaging errors (Peace, 1993).

As a part of any test, as well as any design of any experiment, it is important to do it from a practical viewpoint. Evidently, a minimum of one test result for each trial is required to maintain the balance of the experiment. If the test results are unbalanced (unequal chance for any factor) the experiment requires a special analysis, mainly transformation or regression analysis (Montgomery, 1991). More than one test per trial can be used, which increases the sensitivity and the reliability of the experiment to detect small changes in averages of populations (Mead, 1992). An economic consideration also can be made at this time. If tests are very expensive, then one test per trial can be used. If tests are inexpensive, then more than one per trial can be used. However, the idea is to maintain an ideal reliability and a satisfactory confidence interval, and sample size is the main factor (Coleman and Montgomery, 1993). But, on the other hand, a sample size larger than necessary does not add much to the sensitivity and means higher costs. Shoemaker and Tsui (1992) made some comments about replicating experiments. They suggest that frequently replicating every run is not a wise thing to do, because it is an inefficient way of using experimental resources. Instead, a more efficient way to assess repeatability of experimental results might be to replicate only one or two runs. On the other hand, often it may not be necessary to perform more than five repetitions since groups of five data have one-fifth of the variance of the population and this provides a fair precision for industrial experiments (Lipson and Sheth, 1973; Lewis-Beck, 1993).

The order of performing tests of the various trials should include some form of randomisation. The randomised trial order protects the experimenter from any unknown and uncontrolled factors that may vary during the entire experiment and which may influence the results. Randomisation can take many forms, but the three most used approaches are complete randomisation, simple repetition, and complete randomisation within blocks (Ross 1988). These three were applied to the experiments in this work. The reasoning behind them is explained in the respective experiment Chapters later on.

Complete randomisation means that any trial has an equal chance of being selected for the first test (Ross, 1988). Even complete randomisation may have a strategy applied to it. For instance, several repetitions of each trial may be necessary, so each trial should be randomly selected until all trials have one test completed. Then each trial is randomly selected in a different order until all trials have two tests completed. The experiment will progress on a sequential basis with the opportunity for analysis at the end of each round of repetitions (Peace, 1993). This method is used when a change of test set-up is very easy or inexpensive. Simple repetition means that any trial has an equal opportunity of being selected for the first test, but once that trial is selected all the repetitions are tested for that trial. This method is used if test set-ups are very difficult or expensive to change. Complete randomisation within blocks is used where one factor may be very difficult or expensive to change the test set-up for, but others are easy.

Chatfield (1991) suggests a series of steps or procedures that should be considered when using DoE. It was proposed that Randomisation should be brought into the design but always in a proper way. For instance, in very complicated experiments different levels of each factor were randomised separately instead of doing so to the whole design. Obviously that is wrong and the immediate effect was observed when regression analysis was carried out and variables were supposed to be confounded; in fact, regression takes observations sequentially in the original (natural) order and it is all affected by that "partial" randomisation.

The different methods of randomisation affect error variance in different ways (Peace, 1993). Complete randomisation allows a longer time between repetitions in some trials compared to simple repetition. Because of this, unknown and uncontrolled factors that may be varying during an experiment may make the variation inter-repetition larger with complete randomisation compared to simple repetition (Ross, 1988). Simple repetition, because of the generally longer times between trials, will show larger variation between trials compared to complete randomisation. Increased variation between trials with decreased repetition variation will tend to have some significance in ANOVA when in fact they have not, so complete randomisation is recommended whenever possible (Barker, 1994).

2.3.3 Response Surface Methodology

Another important methodology within Design of Experiments is the Response Surface Methodology (RSM), first introduced by Box and Wilson (1951). Myers et al (1989) define RSM *as a collection of tools in design or data analysis that enhance the exploration of a region of design variables in one or more responses.* RSM predates Taguchi's ideas and has thus not covered noise factors in Taguchi's sense. Nowadays its applications are basically directed to finding regions within the search space where there are demonstrated improvements in response, instead of finding an optimum response (Montgomery and Runger, 1999). Within RSM different families of useful experimental designs, especially first and second order models, can be found which increase practical usability. The most common designs within those families are the Central Composite Design (investigated by Taher (1995)) and the Box-Behnken (Box and Behnken, 1960) designs (Montgomery, 1991). The Central Composite Design remains the family that is most often used due to its properties of Rotatability and Orthogonal Blocking (Montgomery, 1991). The latter refers to that condition in which regression coefficients are orthogonal to block effects, helping analysis to reduce the effect of ambiguous interpretation such as confounding and/or biasing.

Box-Behnken (Box and Behnken, 1960) designs are commonly used in cases in which it is important to use three level factors (Bechofer *et al,* 1995). It is not within the scope of this work to study RSM which it has been widely studied by the statistics community, but to highlight its interoperability with Taguchi methods.

Myers et al (1989) pointed out some differences between the Taguchi approach and RSM. Whilst Taguchi's focus is on improvement and not necessarily optimisation, RSM focuses on finding optimum conditions (or conditions that produce a particular target response) through model-building techniques. They also pointed out the value of Taguchi's approach, even though many think his approach could be improved with more rigorous statistical methods, and that users should learn from the Taguchi approach that system variability should be a major component in the analysis. At the same time, they also note that sequential experimentation is often the most effective way to explore an experimental region.

It is sequential experimentation which opens the door to integration of Taguchi Methods and RSM. Taher (1995) outlines how the sequential experimentation approach uses both methodologies to maximise output response. Within this approach, it is suggested that the Taguchi philosophy calls for experiments at the product or process design stage, whereas other common applications for experimentation, especially RSM, concentrate on optimising the process whilst it is in operation. So, experimentation is not stopped once significant factors have been determined. Taguchi stresses the need to predict the response at the optimum conditions and then verify it with a confirmatory experimental run. Then, it is at the moment of predicting the optimum conditions for the response, once the factorial experiment is completed, when RSM takes action. For this purpose Taguchi Methods are utilised as a basic screening stage so in that way non-significant factors are discarded and only the significant ones are brought forward into RSM (Sanchez *et al,*1994).

Hill and Hunter (1966) suggested a standard procedure that should be followed when doing a Response Surface analysis. The procedure consists of four steps: perform a statistically designed experiment, estimate the coefficients in the response surface equation, check on the adequacy of the equation (via a lack-of-fit test), and study the response surface in the region of interest. The key advantage of this approach is that it allows investigation of a wide range of different design constraints, providing the analyst with detailed information concerning the trade-off between competing design objectives (Hall, 1994) which can include reduction of variation. Evaluation of the response surfaces simply provides function information during the optimisation phase with negligible computing cost (Hall, 1993).

2.3.4 Robust statistics

Recently, there is an increasing awareness that some of the most common statistical procedures, in particular those optimised for a normal distribution, are excessively sensitive to minor deviations from the assumptions, and a group of alternative procedures have been proposed (Huber, 1977). One of the alternative procedures is robustness, meaning insensitivity to small deviations from the assumptions. Those assumptions (such as normality, linearity and independence) are at most approximations to reality which are commonly used in statistics. Although robust methods are designed to minimise the effects of problem data or modelling inadequacies, they are not specifically designed to analyse these problems, but only to mitigate them (Huber, 1977). Diagnostics, on the other hand, are designed to tell why certain cases are unusual and have a large influence on the analysis. They also can tell how a model might be inadequate. Outliers, or modelling errors, when properly analysed, might lead to new understanding and suggest fruitful areas for further research. With some exceptions, researchers in the field of robustness have ignored the diagnostics literature and vice versa (Staudte and Sheather, 1990). This is unfortunate and has caused a lack of information on using these tools together. Neither diagnostics nor robust methods alone are as useful as the combination of both.

A glance at the literature yields rather conflicting statements about the importance and necessity of robust procedures. Some authors, like Stigler (1977) and Hill and Dixon (1982), recommend only slightly robustified estimators, such as slightly trimmed means, and find them hardly superior to the arithmetic mean. Others, like Mallows (1979) and Rocke *et al* (1982), give examples where very robust estimators are needed and are far superior to classical methods. Basically, there is no contradiction. For high quality data or at least precleaned data without any outliers, robust methods are not necessary (Hampel *et al*, 1986). Even for high quality data, good robust methods may still give a noticeable improvement over classical ones, but the size of this improvement is practically secondary and will differ from situation to situation.

There are various groups of tools used to achieve robustness (Hampel *et al,*1986), but commonly the mean absolute deviation and the mean square deviation are used when facility of the analysis is required. The arithmetic mean is a simple, well-understood estimate of location. However, it is highly non-robust, being very sensitive to extreme outliers (Huber, 1977). One simple way to make the arithmetic mean insensitive to extreme points is first to delete or 'trim' a proportion of the data from each end and then to calculate the arithmetic mean of the remaining numbers (Huber, 1977). That is the Trimmed Mean and is considered a robust estimator (Staudte and Sheather, 1990). Depending on the proportion of the sample size that is removed, the trimmed mean can be converted into a normal estimator. For instance, if the proportion equals to 0 then it turns into the usual sample mean; if it is 0.25 then it is the Midmean; and if it is 0.5, the trimmed mean is the median. SAS/INSIGHT software (SAS Institute, 1996) provides several methods for robust estimation of location and scale parameters. These include Gini's Mean Difference (Huber, 1977), Trimmed Means (Staudte and Sheather, 1990), and Winsorized Means (Stigler, 1977). Gini's Mean Difference is a robust estimator of a population scale parameter. For a normal population, it has expected value $2\sigma/(\sqrt{\pi})$, where σ is the standard deviation. Thus, multiplying Gini's mean difference by $(\sqrt{\pi})/2$ yields a robust estimator of the standard deviation when the data are from a normal sample (Minitab, 1988). The constructed estimator has high efficiency for the normal distribution relative to the usual sample standard deviation (Stigler, 1977). It is also slightly less sensitive to the presence of outliers than the sample standard deviation. When outliers are present in the data, Winsorized means are robust estimators of the population mean that are relatively insensitive to the outlying values (Staudte and Sheather, 1990). Winsorization is a method for reducing the effects of extreme values in the sample (Hampel *et al*,1986). For a symmetric distribution, the symmetrically Winsorized mean is an unbiased estimate of the population mean. But the Winsorized mean does not have a normal distribution even if the data are from a normal population (Staudte and Sheather, 1990).

Coleman and Montgomery (1993) gave some guidelines on planning designed industrial experiments. They suggested that response variables should be preferably continuous and can be associated with a target or desirable condition. Furthermore, they recommended Mean Absolute Difference and the Standard Deviation of the Differences as performance measures, because they can be analysed separately or by using the standard deviations to compute weights for the mean analysis. There are some other estimators and approaches to robustness but these are rather complex, for instance, the robust regression procedure and Minimax approach suggested by Huber (1977). However, these may be considered as an only-statisticians field at the present time, and researching such techniques is beyond the range of this work, particularly when the aim is to look for and apply simple but robust techniques to make better products.

2.4 Advantages and disadvantages of Taguchi methods

The Taguchi Method of experimental design has been promoted very strongly in the US and Europe (Ealy 1988), partly because it is thought to be simpler and more defined approach to experimentation, and partly because many successful applications have been attributed to the method. However, the statistical content of it has been of concern of statisticians. In fact, they have been the most ferocious critics of the approach (Lochner and Matar, 1990; Fowlkes and Creveling, 1995).

2.4.1 Aspects Favourable to Taguchi

Although the Taguchi Methodology has many detractors it would not be widely applied if did not appear to deliver in many cases (eg Dunsmore *et al,* 1997; Onuh and Hon, 1998; Khoshooee and Coats, 1998; Grieve *et al,* 1998). Taguchi Methods are more than just DoE, whilst the application of orthogonal arrays offers the immediate benefits of small or minimum amounts of experimentation (see Chan and Ho, 1993; Lyon *et al,* 1991). His experimental strategy made the usage of DoE more practical for engineers and other technical professionals, and he has added some very powerful methods as well. In fact, Taguchi's most noticeable and widely acknowledged contribution to statistics and engineering is his work on variation reduction (Wu, 1992). It is achieved during the parameter design phase, which optimises controllable factors to be robust to sources of variation making use of a simple and balanced experimental strategy.

For instance, Wu (1992) recognised that two of his experimental planning techniques, orthogonal arrays and linear graphs, are either original or have important practical applications. Most of Taguchi's orthogonal arrays are easier-to-use rearrangements of earlier designs (eg Plackett-Burman, 1946) providing a geometrically balanced coverage of the experimental region (Kackar, 1985). Linear graphs, a user friendly and simple graphical tool, save experimenters from doing the tedious work of finding feasible solutions in most small to medium-sized problems (Wu, 1992). Another important tool is SNR which is supposed to contribute to avoiding the problem that the standard deviation has, ie when the mean increases, the standard deviation often increases in the same proportion (Montgomery, 1991) which leads to the uncertainties experimenters with little background in DoE may have. Therefore, SNR in principle might allow studying and reducing variation *relative to the mean.*

From the economic viewpoint, Taguchi's idea of the Loss Function (which is the foundation for SNR) in principle provides a quick insight to variation in the product, as well as loss caused to the society (customer) by these variations. Reduction of these variations, which at the same time reduces the cost and increases product quality, have a direct effect into fine-tuning production processes so parts with less variability can be produced (Peace, 1993). Taguchi methods also help companies to determine the best methods of process control by rapidly determining the optimum settings for a number of control variables, achievable through experiment planning techniques.

Taguchi also focused attention on the costs of lack of quality built in at the design stage. Unfortunately, as Taher (1995) has shown, most published accounts of applications of Taguchi focus on the process rather than design stage.

2.4.2 Aspects Unfavourable to Taguchi

Being the most important part of Taguchi's approach, there are almost no unfavourable elements against his variation reduction concept. However, this cannot be said the same about some of the tools suggested to reduce it. Myers *et al* (1992) pointed out that Taguchi's use of SNR to capture variability has been the subject of controversy. The role of SNR and interactions has been the subject of considerable debate. It has been discussed widely in the literature (Denhad, 1989) that there are often serious objections to the forms of his SNR. Their use can also lead to great loss of information (in the statistical sense) in an analysis and so fail to use all the information in the data (Nelder, 1992), as shown by Taher (1995). Also, Logothetis and Wynn (1989) suggested that SNR is unconvincing as a performance measure whilst it can produce mean bias if the standard deviation and the mean are not linearly connected. Although it is attractive to some experimenters that the use of standard SNR avoids the necessity of thinking about their experiment, this does not pay in the long run. Logothetis and Wynn (1989) commented that the importance of data transformation does not seem to be appreciated or exploited enough by Taguchi. Rowlands (1995) stated the disadvantages of using SNR and suggested an approach employing data transformations using the Box-Cox (Box and Cox, 1964) power transformations.

Box (1988) suggested the use of data transformations as a better alternative to SNR.

In relation to experimental strategies, applied by Taguchi using two key elements (orthogonal arrays and confirmation runs), Wu (1992) suggested that despite the importance of confirmation runs in Taguchi's strategy, problems related to the analysis of marginal means may be serious under particular conditions.

A common, and very valid, objection to Taguchi methods is that the designs offer little protection against the presence of interactions (Fowlkes and Creveling, 1995). The idea is often to explore as many main factors as possible in a saturated design on the grounds of economy. But if a fractional experiment is conducted it is inevitable that information is going to be sacrificed in return for a reduction in the size of the experiment. Interactions cannot be simply ignored; if they cannot be estimated it is because they are confounded with something else, possibly with a main effect. Sometimes these interactions will be ignored when in fact they are important, and this is a weakness in the approach. Analysis is wrong if it does not recognise this. Wu *et al* (1990) investigated these deficiencies and stated that Taguchi arrays can miss important interactions which may lead to poor prediction of optimum settings. Taguchi's suggestion that estimated main effects are not affected by interactions because they are evenly spread/distributed across all of the design matrix columns has been proved wrong (Wu, 1992), leading to the assumption that interactions are not adequately dealt with within Taguchi's framework (Logothetis and Wynn, 1989). Taguchi addresses the problem of interactions among control factors in a different way from classical approaches to experimental design (Phadke, 1992). He dismissed the presence of interactions between factors on the grounds of economy of experimental effort rather than any assurance that is safe to do so (Sacks and Welch, 1992). He also implies that interactions do not occur in real data, whilst experience demonstrates the reverse (eg Taher, 1995).

In order to facilitate the estimation of the specified interactions Taguchi suggested the use of linear graphs. However, in most cases there is no guarantee that the design represented by the graph has any good overall properties (Wu, 1992). Some other ideas, like complex use of ANOVA and large numbers of significant effects in the absence of transformation and modelling techniques, appear to be more complicated than standard statistical practice (Gunter, 1987). Also, Taguchi's failure to take advantage of simple graphics is a disappointment. The failure of his recommended procedures to consider the complicating and distorting effects of a few data points (common in experimental work) through the use of residual analysis or more robust analytical techniques is worrisome (Daniel, 1976).

In relation to experimental designs, Logothetis and Wynn (1989) stated that Taguchi has oversimplified the availability of designs with only a limited list of experimental design offers. This is also supported by Robinson (1993), who suggested that Taguchi's advantages, such as requiring less theoretical knowledge and making it easier to set out the runs for an experiment, conceal some of its weaknesses. For instance, it provides no encouragement to use high-resolution designs, and types of experiments other than factor screening experiments tend to be ignored. Bullington *et al* (1990) expressed their concern that some of Taguchi's designs are not of the maximum possible resolution for a given number of main effects and orthogonal array size. Also, even though Taguchi has proposed some specific and widely advertised novel technical approaches for sensitivity analysis, such as inner-outer arrays, they generally appear to require so much experimentation that they are impracticable (Gunter, 1987). Box *et al* (1988) suggested that many of the techniques of statistical design and analysis Taguchi employs to put his ideas into practice are often inefficient and unnecessarily complicated and should be replaced or modified appropriately.

Box *et al* (1988) criticised the Loss Function by saying that in more complex examples the Loss Function becomes less useful because of the difficulty of characterising and balancing real economic losses. Adams and Woodall (1989) suggested that Taguchi's economic model contains a measurement cost, always based on his main theory of economic loss (expected Loss Function) and loss to the society, but his statistical assumptions are not clearly stated. They also demonstrated that Taguchi's approximations to expected losses can be very misleading under certain conditions.

Chapter 3

Metal cutting case study

3.1 Objectives

Developments in new cutting technologies have been concentrated on automation and control, new cutting tool materials and improvement of machinability conditions (Trent, 1991). The cutting process still needs improvement of machinability and testing methods because the cutting process is still not yet well understood (Trent, 1991). Despite the development of CNC machining and advanced CAD/CAM software, the selection of cutting parameters in industry relies on human judgement aided by empirical results (Stori *et al,* 1999). Recently, two important approaches have suggested ways of selecting, setting and optimising these cutting parameters in an alternative way to Design of Experiments (DoE). The first one (Maekawa, 1998) looks at tribological aspects and the need for a better understanding of cutting process fundamentals as a more rational approach. It is based on correlations and interactions between tribology and cutting processes, all from the viewpoint of computer simulation. Computer simulation and modelling of machining processes also forms the basis of the second approach (Ehmann *et al,* 1997). It is based on a combination of analytical, numerical and/or experimental methods to build an accurate model.

However, most commonly employed metal cutting processes are very complex with factor interactions present and can still benefit from the use of well-designed experimental procedures. In fact, Maekawa (1998) recognised that the commonly applied trial-and-error approach had become useless because of its associated costs, seeing this as the key reason for researching for alternative approaches. As part of an extensive research covering different cases, based on Taguchi (1987, 1993) ideas, Taher (1995) suggested that further investigations of the application of Taguchi and DoE tools during the design process are required in different engineering areas. This work resumes some parts of Taher's research, aiming to integrate his methodologies with other optimisation tools and applications. Taher (1995) looked at different aspects of DoE generating substantial amounts of data which can be positively exploited. Data from his full designs remain available for further investigation, and an extraction of different Taguchi arrays can be tested with reference to the full design outcomes in terms of both significant effects and robust design settings. He also examined and used repetitions as a tool for control of process variability and suggested that a larger number of repetitions (more than four) could possibly result in better variability estimation.

In this case study, the objective is the optimisation of the milling operation as a typical metal cutting process through DoE. The optimisation aim is to define the best machining conditions in a manufacturing environment, able to represent a typical batch manufacturing process, through Taguchi, conventional DoE techniques and the following goals:

(a) Determine significant factors affecting surface finish production and other properties, such as hardness, in specific conditions particular to milling processes.

(b) Study the effectiveness and interoperability of Taguchi designs, including comparisons between the outcomes of both equivalent Taguchi array and the ideal full factorial design.

(c) For a particular quality response such as surface finish, study and establish differences between different approaches to measuring these, eg parallel and perpendicular to milling direction or measurement methods for surface roughness and determine their possible effects on outcomes.

The following questions are typical of those to be answered in the industrial application context:

(1) Considering surface finish (roughness) and hardness as quality responses, which factors/interactions are considered to have significant influence on these responses? Which controllable factor settings should be considered as response enhancing?

(2) About (c) above, is there any significant variation between both methods? If so, what may be causing that variation? What could be the consequences of it?

3.2 Background to the case study

In most machining operations the machinability of a material can be assessed by many quality criteria, which are generally associated with surface integrity, and surface finish is therefore often an important criterion for machining operations (Shaw, 1984). However, most quality criteria for metal cutting are conflicting, thereby difficult to optimise without formulating solutions based on multi-objective optimisation techniques. The general approach is to work on one quality criterion, such as surface roughness, but this may not be enough for more complex and demanding problems. As an alternative approach to some other models, Taher (1995) utilised contour and desirability approaches for multi-response optimisation, which are based on model building through multi-regression analysis (Montgomery and Elizabeth, 1992).

Clark and Grant (1992) indicated the importance of surface finish for interchangeable manufacture. Surface finish is one of the essential attributes of the product quality known to greatly influence properties such as fatigue strength and wear resistance, which convert it into an important design specification. A good surface finish is important not only for cosmetic purposes but it also has an effect on the life of the component (Loh *et al*, 1991). Steeds (1964) pointed out that imperfections in surface finish, such as small holes, scratches, tool marks, etc., create stress concentrations which reduce the fatigue strength of the material. The effect of these imperfections can be minimised by employing some common finishing processes (eg polishing) to improve surface finish after machining. However, these can be costly at times and increase the amount of resources required. For this reason, the aim of this study concentrates on ways of improving surface finish production "right first time", through the application of "off-line" quality methods (eg DoE, Taguchi, etc.).

Mills and Redford (1983) suggested that there are five mechanisms which contribute to the production of a fine surface finish. These are the basic geometry of the process, the efficiency of the cutting operation, the effective clearance angle on the cutting tool, the stability of the machine tool, and the effectiveness of removing swarf. Modern CNC machines offer capabilities in relation to these issues compared with traditional/older machines. In CNC machines stability is rarely an issue where structure provides rigidity to the cutting tool. Good clamping therefore reduces some of the possible causes of vibration. However, vibration is still present once the tool starts to wear after intensive use or once it has reached the end of its normal life. At the same time, these machines provide efficient swarf-removal capabilities, either through the cutting fluid (jet) or simple gravity, assisting in reducing the marking of the surface which often results in a better surface finish.

In relation to these mechanisms, Mills and Redford (1983) pointed out some of the factors which influence surface finish production. They referred to tool geometry and feed rate as factors influencing the basic geometry of the cutting surface. Cutting speed is also considered important, particularly if it is set high. Depending on material type, other factors should be considered, such as tool rake angle and cutting fluid, especially when combined with high cutting speed. Small tool rake angles have an adverse effect on the surface, so increasing the rake angle tends to improve the machining conditions and surface finish. Even when cutting at high speed, some materials produce conditions where formation of built-up-edges have an adverse effect on surface finish, a situation which can be improved by reducing the feed rate and depth of cut, and applying cutting fluids. In this respect, Krar *et al* (1977) suggested there is a relationship between high temperature and a rough surface finish. Metal particles have a tendency to stick to the cutting tool at high temperatures forming built-up-edges and cutting fluids may contribute to stabilise the workpiece temperature. Among the two basic types of cutting fluids, cutting lubricants and soluble oils (coolants), Mills and Redford (1983) commented that in virtually all cases both types of cutting fluid tend to improve the efficiency of the cutting process and thus tend to lead to an improvement in surface finish, as well as an increase in tool life through a decrease in cutting temperature. Krar *et al* (1977) agreed with Mills and Redford on the factors affecting surface finish during a machining operation. They include the feed rate, nose radius of the tool, cutting speed, and the temperature generated during machining.

Most of the factors already mentioned have an effect on tool life, particularly cutting speed, feed, depth of cut, clearance angle, tool, nose radius, etc. However, if these were all to be considered the number of tests required to cover a reasonable range of cutting conditions would be prohibitive. Equations have been developed to solve this and reduce the amount of testing (Mills and Redford, 1983), which, combined with simulation methods, results in a good alternative to physical testing. Nowadays, the role of machining process modelling is becoming universally recognised in industry, though it is presently in a transitional period moving from just a curiosity in the academic community towards a well-accepted role in engineering and industry (Ehmann *et al*, 1997). Simulation methods ranging from non-linear programming optimisation techniques (Stori *et al,* 1999) to Neural Networks (Stark and Moon, 1999) have been applied successfully in this quest, although much work needs to be done in this dynamic area of metal cutting research. Stori *et al* (1999) used simulations in parameter selection decisions, involving selection of process parameters and surface finish requirements for the final surface of a milling operation, mostly optimised through numerical methods, proving they can be efficiently applied if constraint models are successfully built. Basic and applied research results have now been brought together, with the aid of the computer, to provide reliable predictions of the performance of the cutting process and the impact of the process on product quality and process improvement (Ehmann *et al,* 1997). When physical testing is required or preferred there is always room for DoE and other related techniques in order to reduce the amount of testing.

From the viewpoint of costs, the operation and scheduling of machining processes is also affected by and dependent on cutting conditions and vice versa. In fact, Mills and Redford (1983) indicated the three most common criteria used as a basis for the successful operation of a machine tool. They are minimum cost, maximum production rate, and maximum profit. The economic batch size is controlled by the cutting conditions, and whatever criterion of performance is chosen there is no doubt that optimising cutting conditions will lead to a better and more efficient metal removal operation. Costs for milling cutting operations are much lower than their equivalents in turning (Mills and Redford, 1983). Thus, it is reasonable to assume that for milling, improvements in machinability can be reflected in improved performance (lower cost production) but that this will not be as significant in milling as in turning. Nevertheless, knowledge of the machinability characteristics is still very important since it is only from these that appropriate cutting conditions can be chosen.

Maekawa (1998) illustrated (Fig. 3.1) most of the relationships between cutting phenomena, which open the door for further understanding of the process. Several factors must be considered when setting up a milling job, including (among many) the type of milling operation, speeds, feeds, depth of cut, and safety. There is a very dense network of relationships among factors, which in most cases interact having high incidence on the process itself. In the following, there will be an attempt to isolate the most important factors that affect milling operations and, especially, surface finish production. However, it is advisable to keep in mind that factor inter-relationships are a commonplace in metal cutting processes.

(a) Milling method

Milling cutter problems are commonly caused by excessive heat, built-up-edges, cratering, edges chipping, abrasion, clogging, and work hardening of the piece (Mills and Redford, 1983). Krar *et al* (1977) suggested that cutter choice should be done in accordance with the milling method to be used. For instance, conventional milling is used on workpieces where minimum shock is desirable when the cutter enters the work. Baril (1987) commented on several advantages of climb milling over conventional milling. For instance, chips pile up behind the cutter instead of in front and are less likely to be carried by the cutter teeth, reducing the possibility of damaging the surface. At the same time, the cutter wears less because chips are thicker at the start of the cut regardless of cutting speeds used. On the other hand, in some situations conventional milling may be advantageous over climbing milling because there is a lower impact on the cutter at the start of the cut. Consequently, he stated that climb milling would generally produce a better finish than conventional milling. Dallas (1976) pointed out other advantages of climb milling which includes smoother machine operation (less tendency to chatter in some situations), better load conditions on cutting edges of carbide cutters, thereby reducing serious damage to cutting edges, and possible use of higher speeds and feeds. Finally, Baril (1987) asserted that the importance of using any of these methods consists in the way cutting forces are dealt with. These are related to impact forces, clamping, and tool life that could affect surface finish depending on which direction is taken.

(b) Cutting speed

The speeds used for milling-machining cutters are much the same as those used for any cutting tool. Several factors must be considered when setting the cutting speed to machine a surface. Krar *et al* (1977) considered as the most important ones the material to be machined, cutter type and material, finish required, depth of cut, and the rigidity of the machine and the workpiece. When tool life and wear are relevant issues then lower speeds are recommended, otherwise they recommended the use of higher speeds for better finishes and light cuts. Baril (1987) also suggested a number of factors to be considered before choosing a speed of feed in milling. Hardness and the toughness of the cutter used are considered as major factors. Also Brinell hardness of the material shall be taken into account (Walsh, 1994). Other factors are the rigidity and general condition of the machine being used, even though the effect of these factors is reduced with the use of CNC machines. Baril (1987) pointed out the importance of impact forces on selecting tool speed. Low speed may deliver very damaged surfaces because of increased time-contact between tool and piece. Materials to be cut offer resistance to penetration by the cutting edge (tool). Dallas (1976) suggested that higher cutting speeds could be used when cutting resistance is low as in the case of aluminium. Dallas (1976) also advised a lower feed rate in preference to a high cutting speed whenever a fine finish is required.

(c) Feeds

Milling feed can usually be determined by certain given equations, which are a function of geometry of the cutter (number of teeth in the milling cutter), amount of material removed by each tooth, and the cutter speed (Krar *et al*, 1977). Dallas (1976) pointed out feed rate as a very important factor to consider since production rate is directly related to it and because one of its "components" (feed per tooth) is one of the important factors to be selected in milling operations. Feed per tooth will determine the amount of material removed by each tooth, the tooth load on the milling cutter teeth, surface finish by controlling the tooth-mark spacing, and cutter life as affected by either too large or too small feed per tooth (Dallas, 1976). In the same way, it has been determined that less feed should be used if better surface finish and deep slotting cuts are required. Otherwise, tool protection against excessive wear is more important so a bigger feed rate should be used. It is also known (Kalpakjian, 1997; Trent, 1991) that feed rate has an influence on impact forces in the process, as well as on tool life.

(d) Cutting fluids

Cutting-fluid requirements for milling operations are best understood when compared with the turning process (Dallas, 1976). Even though an excellent opportunity for cooling is afforded, milling is generally done at lower speeds than turning because of chatter, shock loading and finish. Milling is generally more severe than turning operations. Cutting fluid is best applied in the milling operation so that high-speed cutters, workpiece, and chips are flooded with a large volume of fluid to provide maximum cooling (Dallas, 1976). Krar *et al* (1977) suggested that coolant should be used whenever possible to reduce machining friction and heat that will shorten the life of the cutter. The use of coolant in metal cutting processes is justified by the relationship between high temperatures during machining and rough surface finish in some kinds of materials. It is caused because coolant prevents the process from overheating avoiding metal particles adhering to the tool affecting the surface as well as the tool. Krar *et al* (1977) suggested aluminium and some alloys might be machined dry.

(e) Depth of cut

Chip size production has a direct incidence on surface finish. When depth of cut is increased bigger chips are produced, which, depending on the efficiency and the speed of the metal removal operation, may affect surface finish negatively. It is also possible that the combination with metal cutting methods has a positive effect on surface finish through effectiveness of swarf removal. Taher (1995) used constant depth of cut in his turning experiments, among other reasons to reduce by one the degrees of freedom. Transferring depths to milling should be considered under the grounds of depth of cut being an associated factor to feeds in milling (Krar *et al,* 1977). Dallas (1976) indicated depth-of-cut ranges depending on the type of finish aimed at. For roughing operations it may range upward from 1/8 inch (3mm); in finishing operations it may vary from a few thousandths of an inch to 1/16 inch (1.5 mm).

(f) Number of cuts

Abrasion is one of the most common causes of milling cutter problems, and certainly affects surface finish (Mills and Redford, 1983). Increasing the number of cuts also increases the probability of surface abrasion. Obviously, this factor and its consequences (e.g. abrasion) are also associated with other factors like tool type, milling method and cutter speed, making this relationship an interesting target to study. Increased number of cuts, on the other hand, could enhance surface finish through removal of loosened chips and swarf. Dallas (1976) mentions that several cuts are often taken at a faster feed rate instead of one cut at a much lower feed rate in order to improve production efficiency.

(g) Tool type

The basic geometry of the process was described by Mills and Redford (1983) as one of the key mechanisms of metal cutting. Tool selection has two main requirements for surface finish, which are wear resistance and toughness (Herman, 1990). Also, geometry parameters such as shape are very important for the efficient removal of metal. For these reasons, two different tool types, with similar geometry and material, were tested in this case study. The 2-flute end mills are used for general purpose milling because they provide good chip clearance and remove metal quickly. The 4-flute end mills are generally used for finish cutting providing better quality surfaces. Both cutters were utilised in different stages of this case of study. In addition, they are similar to the factors in the turning study of Taher (1995) such as tool shape and type.

(h) Diameter of cutter and width of cut

In face milling it is important to select a diameter of cutter suited to the proposed width of cut if the best results are to be obtained (Dallas, 1976). Cuts equal in width to the full cutter diameter should be avoided, if possible, since the chip section at entry of the teeth will result in accelerated tooth wear from abrasion, plus a tendency of the chip to weld or stick to the tooth (Drozda, 1983). This is detrimental to surface finish and a good ratio of 5:3 is suggested. Radulescu *et al* (1997a, 1997b) suggested that the effects of the workpiece width and cutter diameter can significantly affect regeneration and forced vibration mechanisms during machining.

(i) Angle of entry

This is controlled by the relationship of the cutter centreline to the edge of the workpiece (Walsh, 1994). High positive entry angles tend to place initial cutter-workpiece contact at the extreme point of the tooth or cutting edge (Dallas, 1976). This can result in chipping or breakage with carbide inserts, so negative entry angle is a more desirable condition (Drozda, 1983).

(j) Material

The tensile strength, hardness, and ductility of the material being cut have a direct effect on the mechanical characteristics of the process. Dallas (1976) related these property effects to power requirements in milling. For instance, in this experiment aluminium was the choice due to its machinability in normal conditions (ie, lack of overheating). Some researchers (Olsen, 1965; Dontamsetti and Fischer,

1988) studied the effect of the hardness of the workpiece on the surface finish quality. They observed that surface roughness improves as hardness increases.

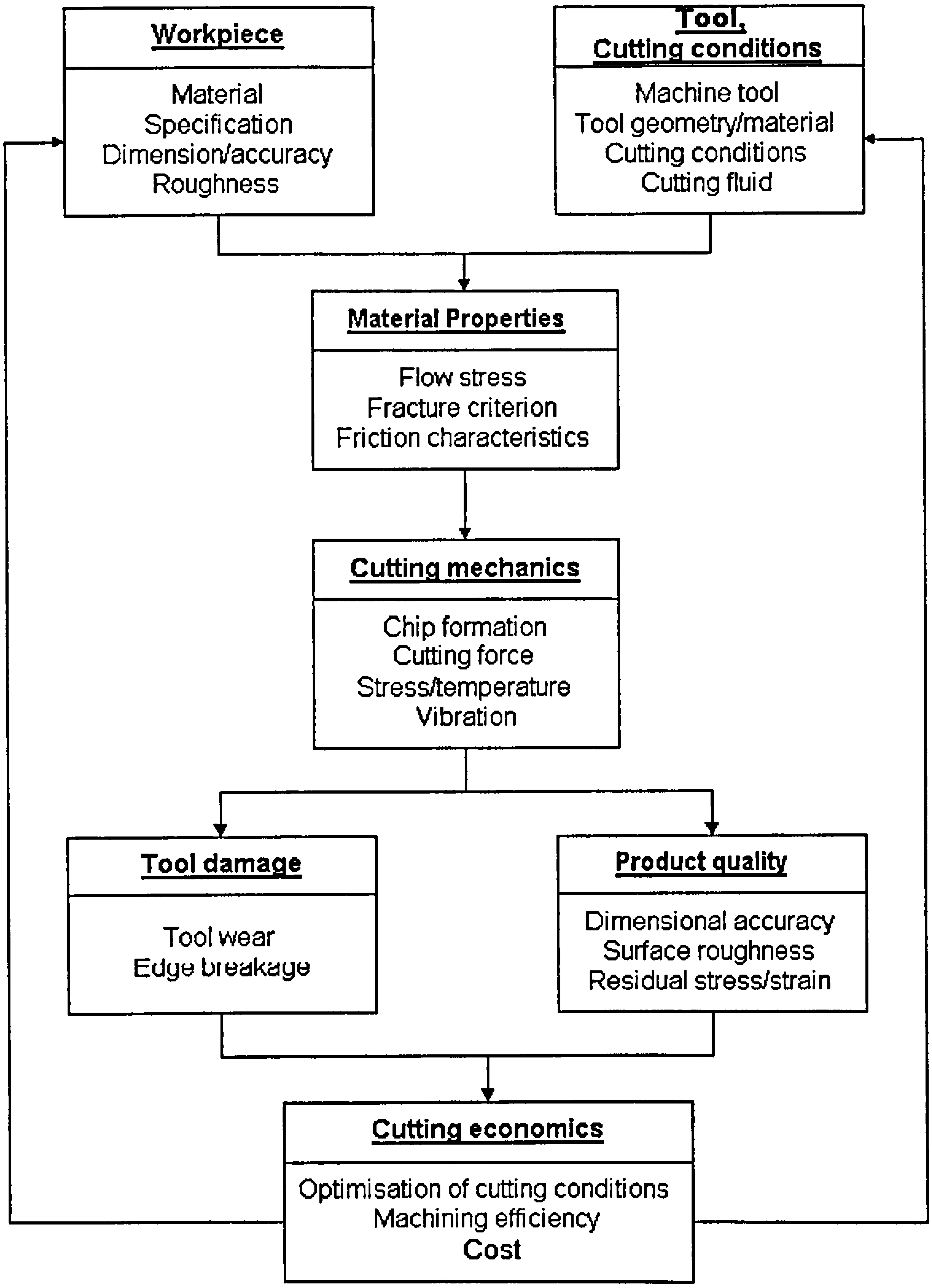


Fig. 3.1 Relationships between cutting phenomena (from Maekawa, 1998).

3.3 General Methodology

This methodology was substantially based on an approach suggested by Montgomery (1991) for planning experiments. The original approach encompasses seven basic steps: Recognition of and statement of the problem, Choice of factors and levels, Selection of the response variable(s), Choice of experimental design, Conduction of the experiment, Data analysis, and Conclusions and recommendations. Due to very strong links between the three main experiments in this case study, Montgomery's approach (Fig. 3.2 (a)) was adapted with simplicity in mind in order to cope with the main objectives of this work. The common framework consists in grouping activities in three main stages facilitating comparisons and evaluations between procedures as well as a stable base to guarantee sequential experimentation at all levels. These stages are experimental design, data acquisition, and data analysis. Each of these stages (Fig. 3.2 (b)) can be broken into a series of steps to simplify and speed up the whole experimental process (Fig. 3.2 (c)).

The suggested framework (Fig. 3.2 (c)) initiates the process with the heart of the conceptual process, which is the experimental design stage. The experimental design stage starts as every normal experiment: recognising/identifying and defining the problem. This step is more than fundamental for the Experimental Design stage. It sounds trivial but it has been part of the unavoidable classic philosophical approach for experimentation since ancient times. In many cases where experimenters claim they cannot find the causes of the problem nor improve the product or process, the reason may be a lack of understanding of the problem associated with an unclear and/or fuzzy definition of it. A solid and clear definition of the problem is the leading path to a plain identification of the variables surrounding the object of study.

Recognising, defining and stating the problem paves the way for the next step: the variable selection process. Brainstorming for variables enhances the selection process, considering and accepting all possible causes of noise. This practice offers the benefit of not ignoring variables that may seem inappropriate on their own but whose interaction with other variables may be important. Also, this brainstorming process may be useful for tailoring the environment surrounding the process or product. This environment, which is generally the operational one, sets the conditions for defining and selecting response(s). At this point, the outcome of the brainstorming process can be directed in two different ways: selecting the response(s) as well as the final choice of factors and levels. Ideally, the task of selecting the response(s) should be a direct effect of the problem definition. But with the introduction of a brainstorming process the whole procedure opens up the possibilities of studying other response(s) not considered initially. At the same time, reducing the choice of factors (selected during the brainstorming) to a manageable and practical number would benefit the experiment making it less costly. Criteria for this reduction rely on the supposed influence of the selected factors on response(s). This approach is suitable for experiments where resources are the main constraint, leading in most cases to substantial cost reductions through experiment length reduction. Outcomes from these two steps will produce valuable information, enough for offering guidance on which choice of experimental design may be more convenient. Therefore, the next phase (choice of experimental design) is fundamental because it involves the way data are going to be generated, protected against biases, and analysed. It also determines the length of the experiment, and the way variables, factors and responses are going to be treated. Finally, conducting the experiment can be a straightforward procedure if the experimental design is well conceived. It may only consist of taking care that environmental parameters are under control and that the whole procedure is experimental design compliant.

Data collection, classification and organisation follow once the experiment is carried out and completed. Whatever is going to be the output of the experimental phase, data have to be gathered and organised prior to the analysis phase. The data analysis phase, which is the next step, is closely related to the experimental design. Following DoE methodologies, or any other alternative statistical methods, like those studied here, would be the most common choice for this phase with *any* type of experiments. The adequacy of the method chosen for the data analysis may prove to be the determinant for reaching any conclusions or recommendations.

Based on this case study, two parallel experimental procedures were developed based on the general framework (Chapter 1). The first outlines the plan for a complete metal cutting experiment (Milling). The second, which is studied later (Chapter 6), utilised data sets to study the integration and interoperability of Taguchi methods with some of the most common analysis tools. Those data sets were based on data both from Taher's (1995) turning process and also the milling experiment carried out in this work.

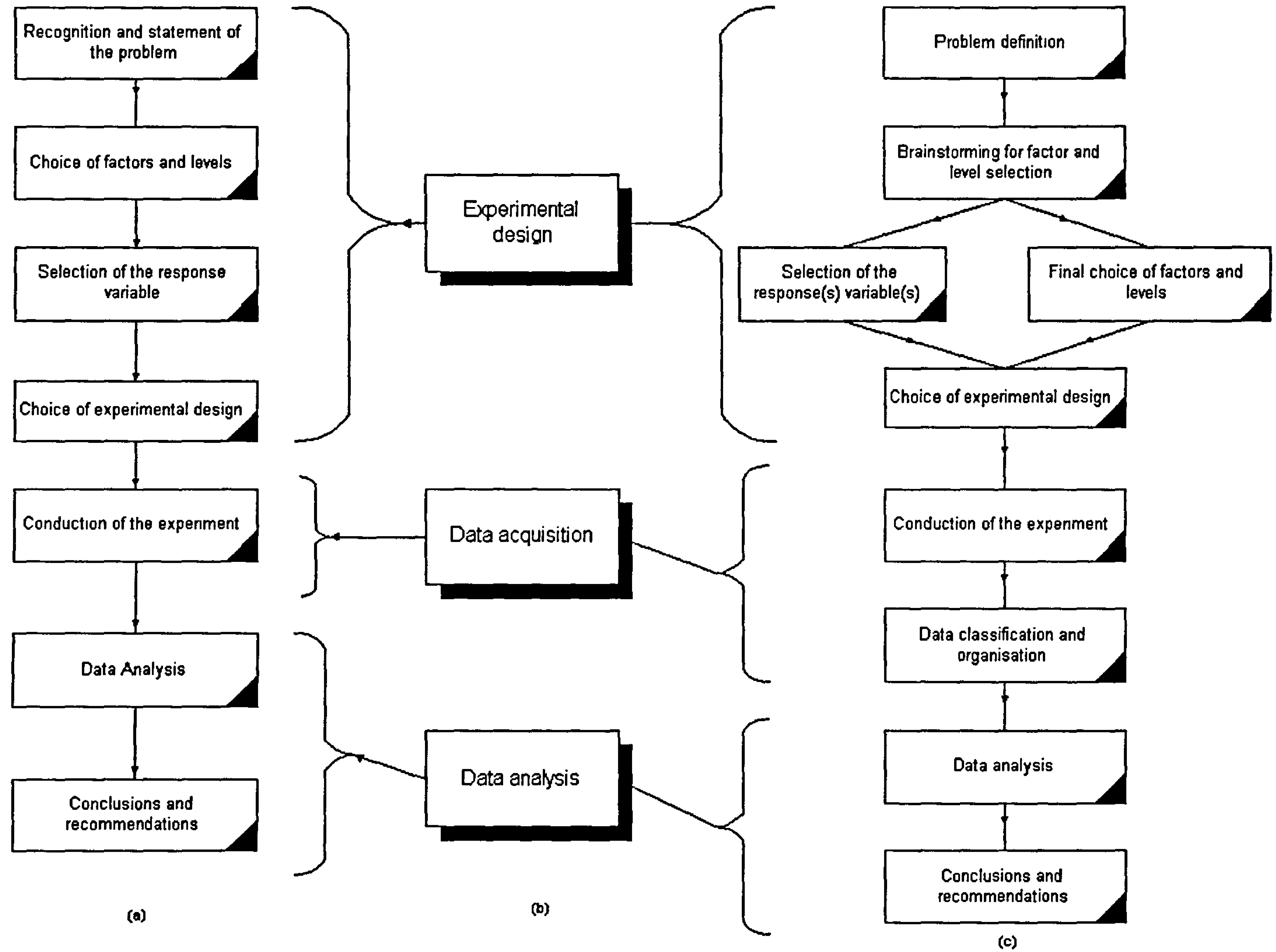


Fig. 3.2 Experimental methodology layouts

3.4 Milling machining case study

3.4.1 Experimental design

Taher (1995) carried out investigations of the Taguchi approach applied to metal cutting. He set up a series of experiments on finishing properties of metal cutting processes, selecting turning as the machining process to study. Wondering whether Taher's (1995) studies and applied techniques could be tried out on a different metal cutting process was the core of problem definition in this experiment.

The proposed methodology suggests carrying out the brainstorming session from scratch. However, brainstorming in its conventional sense is not easily done within the framework of a single student higher degree research programme. In this study, "brainstorming" will refer to an alternative process which involves collecting ideas from the previous literature followed by discussions with supervisor, technical staff and other staff and students with interests in the field. In addition, special considerations were made regarding factor and response selection. Taguchi's statements on the importance of the experimenter's experience and knowledge about the process as one of the most important elements in the whole philosophy (Condra, 1995) should not be forgotten. The starting point was the set of factors and responses utilised by Taher (1995) in his turning experiment, where he considered surface finish as the main quality characteristic response. Taher (1995) made a very extensive review of factors affecting the production of fine surface finish in turning, though, with a different metal cutting process for this experiment, further research was necessary for factors affecting the milling process. The fact that they are both metal cutting experiments means common variables and mechanisms (Section 3.2), but experimenters might only expect similar variable behaviour if equivalent factors are chosen. During this brainstorming process factors were considered in three different fronts: those affecting the process itself, those related to the material, and those related to the design limitations of the machinery (Section 3.2), resulting in eleven factors having incidence on the process. These factors were: milling method, cutting speed, feed, cutting fluids, depth of cut, number of cuts, tool type, diameter of cutter, width of cut, angle of entry and material to be machined.

The importance of surface finish for component reliability within manufacturing processes has been widely acknowledged (Section 3.1). Therefore, surface finish (roughness), as well as hardness as a secondary quality response, were the responses selected for this case study. Roughness can be measured using different methods, including the bearing area approach or average height measures such as root mean square average (R_q), ten point peaks to valley height average (R_z), and centre line average (R_a). Despite the possible superiority of bearing area or other methods, centre line average (R_a) was the choice because it guarantees uniformity to values along the central line taking in consideration more points than other average height methods, which means greater robustness and, therefore, turning it into the most widely used method in industry due to its simplicity (Kalpakjian, 1992). The value of R_a is determined within the evaluation length (including several sampling lengths), which is a function of range and cut-off value (Mitutoyo, 1989). The cut-off length is standardised by British Standards (BS

1134, 1990) at 0.25mm, 0.8mm or 2.5mm. BS 1134 (1990) suggests suitable cut-off values depending on the R_a (roughness) value (Table 3.1).

The number of factors identified during the brainstorming process was reduced to a feasible minimum for experimentation taking as the main criterion the response selected (surface finish). A summary of the factors and their levels selected is shown in Table 3.2. From the original brainstorming factors, milling method, cutting speed, feed, cutting fluids, depth of cut, number of cuts and tool type, correspond in Table 3.2 to direction of cut (DIC), tool speed (TS), workpiece travelling speed (WS), coolant (C), depth of cut (DC), number of cuts (CL) and tool type (T), respectively. The other four factors were restricted by practical constraints and therefore remain constant for these experiments. Diameter of cutter and width of cut were fixed for a standard testpiece and are an aspect of the tool type factor for the purposes of this experiment. Material to be machined also remains fixed as only one material (aluminium) was used during the experiment. In a practical industrial situation, natural variability within and between batches of material will be a noise factor, as defined by Taguchi. An essential feature of the Taguchi approach is that the experiments are not intended to identify how important or otherwise such noise factors are, but rather to choose controllable factor settings that minimise the effect of such unavoidable noise factors on target outcomes.

The equipment available restricted level selection of three of the factors (tool speed, coolant and workpiece travelling speed). Choice of levels for the tool speed factor was limited by the CNC machine capabilities, which allow speeds within the 2000-4000 rev/min ranges. A similar situation occurred for the workpiece travelling speed which was also limited by the CNC machine to two different stable speeds (203 and 330 mm/min). Taher (1995) investigated different levels of coolant use (more or less fluid during the cutting process). Though the type of cutting fluid may have a significant effect on machining responses, it was not feasible at the time to vary this. Therefore, in this case, since the use of coolant is supposed to influence surface finish positively, to turn it into "control" factor results simply in the option of using it or not. Selection of other factor levels for depth of cut, direction of cut, number of cuts and tool type was based on literature suggestions and, in some cases, on very obvious choices (eg. only two options for direction of cut: climbing and conventional). As can be seen, the final choice of factors includes only controllable factors. Environmental/uncontrollable factors, like method of clamping (operator-skills dependent), environment temperature/pressure/humidity, etc., were left aside as they are present in every workshop normal operational conditions and it was not practical to vary these systematically during the test programme.

Once both factors and responses were defined, the selection of the most adequate experimental design(s) have to be made. Sequential experimentation strategies, as studied by Taher (1995), would be the ideal approach for most of the experiments for optimisation through model building with a large number of screenable factors. However, the low number of factors involved in this case study as well as the objectives sought suggested the comparison between full factorial and Taguchi arrays.

Since the seven factors were to be studied at two levels so as to limit the size of the full factorial to a practical level, the total number of runs in the full factorial experiment would be $2^7=128$ runs. A typical Taguchi array that might be utilised in this scale of experiment would be an L_{16} with only 16 runs There are only 15 degrees of freedom available for estimation in this Taguchi design. As has been pointed out already (Section 2.2.2), interactions are confounded with main effects. Allocation of the main factors to the different columns of the L_{16} array was done through the use of linear graphs (Fig. 3.3). For this type of array, there are six types of linear graphs offering a maximum number of main factors (that can be studied without confounding) ranging from 5 to 10. Two types of linear graphs were chosen (Fig. 3.3): LGII and LGIV (these correspond with Taguchi (1987) nomenclature). The LGII distribution allows the allocation of a maximum of 7 main factors in the Taguchi array, leaving the eight remaining columns available for error terms. Analogously, the LGIV distribution allows up to 8 main factors "without" confounding.

R_a (range in μm)	Suggested cut-off value (mm)
0.02-0.1	0.25
0.1-2.0	0.8
2.0-10.0	2.5

Table 3.1 Recommended cut-off values for R_a
(From BS 1134, 1990)

FACTOR	LABEL	LEVEL 1	LEVEL 2
Tool speed (rev/min)	TS	3200	2700
Workpiece Travelling speed (mm/min)	WS	203	330
Depth of cut (mm)	DC	1	0.5
Coolant	C	Off	On
Direction of cut	DIC	Climb	Conventional
Number of cuts	CL	1	2
Tool Type	T	4-flute	2-flute

Table 3.2 Milling case study: summary of factors and level selection.

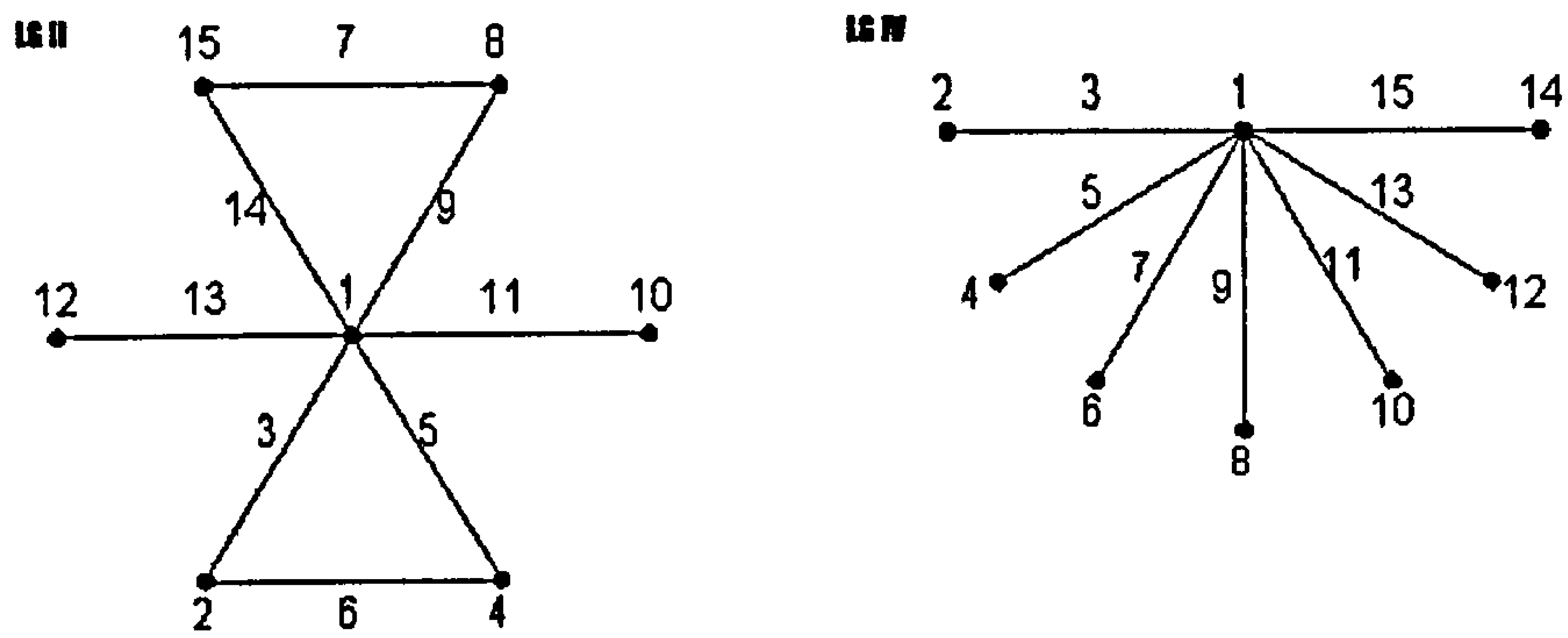


Fig. 3.3 Taguchi's L_{16} linear graphs (from Peace, 1993).

3.4.2 Data acquisition

3.4.2.1 Conduction of the experiment

Blocking as well as randomisation techniques were applied to this experiment in order to reduce the effects of variation (Ross, 1988). Blocking techniques were also applied as a way to separate the full factorial design into two blocks, emulating in this way production batches in workshop normal operation conditions. Besides variation reduction, an important reason to do blocking is mainly operational. Frequent tool changing caused by randomisation is time consuming. Coolant may be an alternative to tool type as on-off swaps could be costly and also time consuming but not as much as tool type. Thus, tool type factor was the obvious choice for doing the blocking. The first block consisted of the first 64 runs out of the fully randomised full factorial experiment, having tool type factor fixed at one level (using the 4-flute tool type). Analogously, the second block consisted of the remaining 64 runs in the design. Randomisation applied in this experiment is the type called *complete randomisation within blocks* (Section 2.3.2). Randomisation was carried out using Statistical Analysis Software (SAS Institute, 1991), which provided a detailed list with runs and level settings.

Besides randomisation and blocking techniques, there was also scope to study repetitions. As has been suggested (Section 2.3.2), repetitions may have an effect on the reduction of the variation in the sample. Therefore, right after obtaining data for the first block, a preliminary study (Chapter 6) was carried out to determine an appropriate number of repetitions to be used in the remaining block of this case study. The first block of the experiment was carried out with eight repetitions per run. Following analysis, the second block was made of samples with four repetitions per run as suggested by the preliminary study (Section 6.4).

Material preparations were made prior to machining. Each one of three aluminium bars ordered in the same batch (two bars for the first block of the experiment and one for the second block) 3.5m long were cut into 35 equal parts which became the workpieces after they were machined to match design specifications (Fig. 3.4). The workpiece shape (Fig. 3.4) ensures adequate clamping on the vice thereby minimising vibration during milling and subsequent chatter problems. The two transverse holes made in the workpiece were for facilitating clamping, though it is not known whether these two holes may help to dissipate energy so part of the stress may be liberated. The workpiece has been designed so machining can be carried out on two of the faces (Appendix A1) giving four repetitions on each face (Fig. 3.5). Thus, the first block required 64 workpieces (one per each run of eight repetitions) and the second block 32 workpieces (two runs on each workpiece at four repetitions each).

All the machining was conducted on an automatic Cincinnati Milacron Arrow model 750 with multi-tooling change facilities. The machine has three sliding axes (X, Y, Z) and operates automatically following instructions contained in loadable programs. Vertical movement is provided by the travel of the rotating spindle, whilst movement in the horizontal plane is done by the sliding saddle (Y axis) and the supporting table itself (X axis) (Cincinnati Milacron, 1994). The supporting table is the actual working surface for clamping of the workpiece. The milling operations were carried out in the presence of water based coolant whenever required by the experimental design. The CNC machine has a special system for handling coolant recovery, using a circulating pump and a filter for cleaning purposes easing re-circulation of fluid, and a jet to direct fluid to the tool. The cutter used was a standard die sinking with square geometry. Program to handle the CNC operation was prepared and loaded into the machine (Appendix A2) to perform the machining according to the geometry of the workpiece and with the settings already defined in the experimental array.

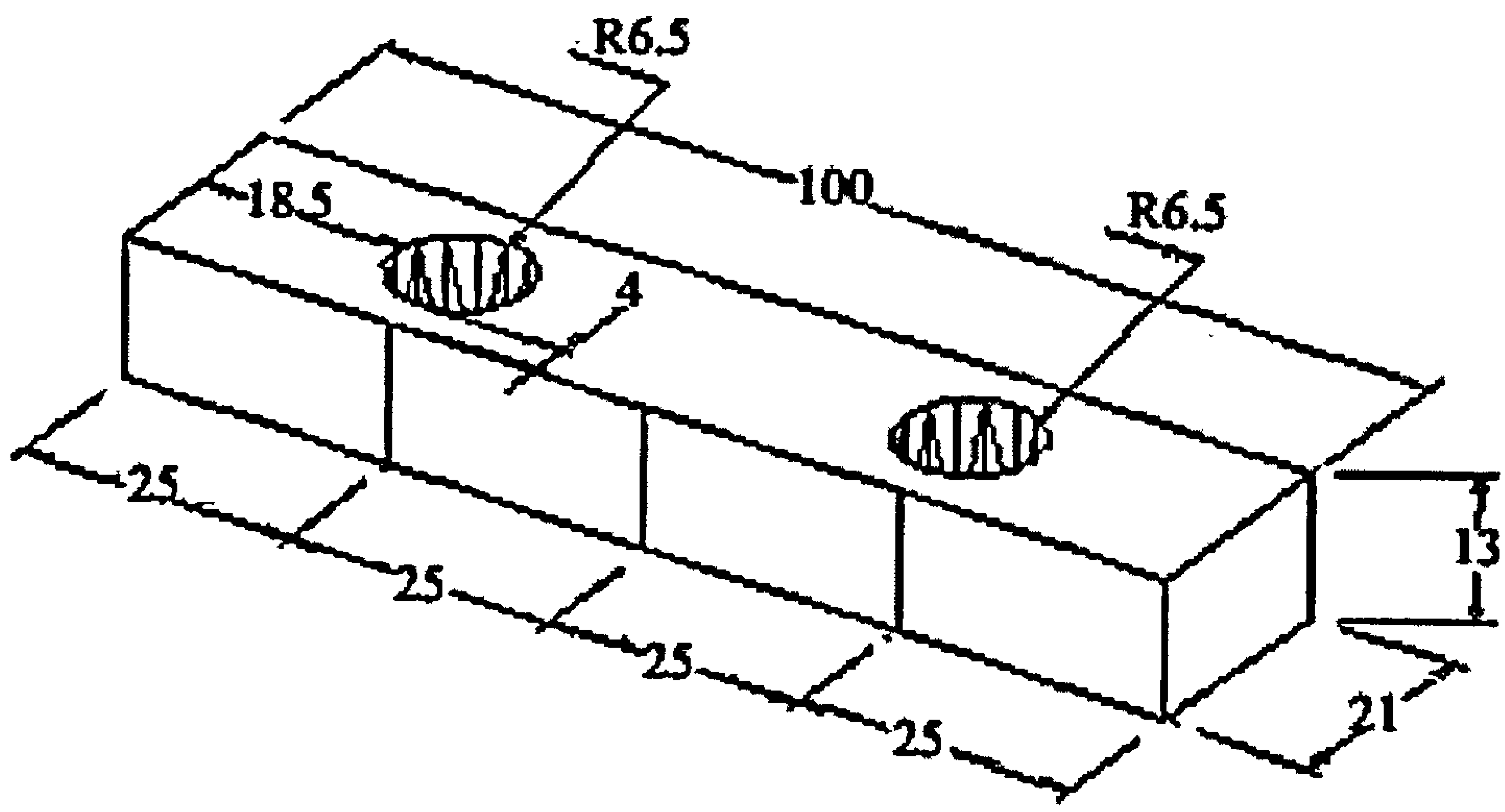


Fig. 3.4 Workpiece design and dimensions

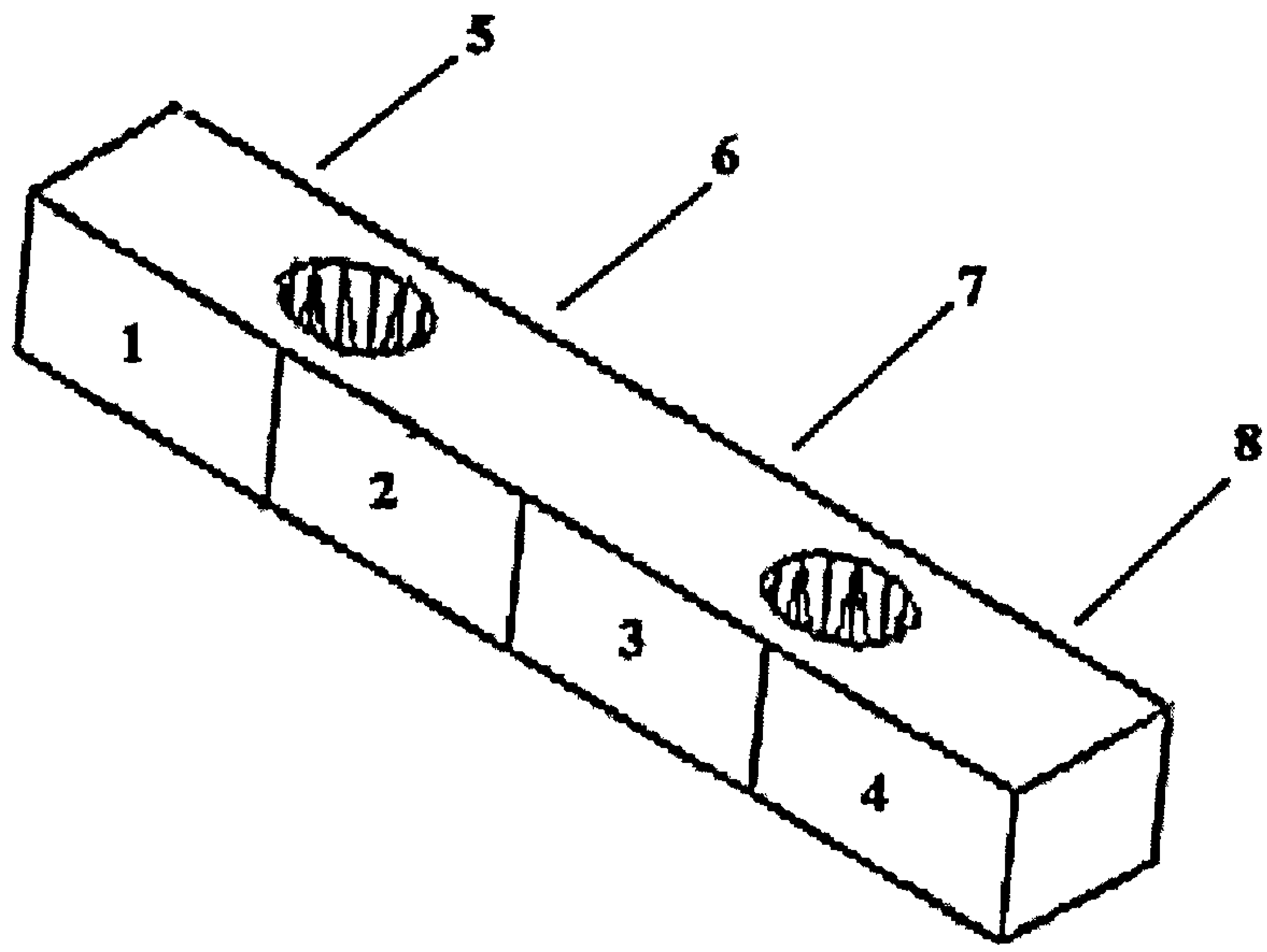


Fig. 3.5 Workpiece machinable areas for experimentation.

3.4.2.2 Data classification and organisation

Galyer and Shotbolt (1990) suggest that there are two kinds of methods to measure surface finish: comparative and direct measurement. Due to the characteristics of this experiment it is advisable to use direct measurement. In this case a probe type instrument (light weight stylus), specifically a Mitutoyo Surftest 402 series, was used. This measuring unit has two parts, a display-control unit and a detector. For details on specifications, figures and operation conditions see Mitutoyo's operation manual (Mitutoyo, 1989). The value of R_a is determined within the evaluation length (including several sampling lengths), which is a function of range and cut-off value (Mitutoyo, 1989). Taher (1995) investigated through a full factorial experiment different combinations of these two parameters finding that a cut-off value of 0.8, a range of 50μm and a sample length (parameter required for R_a estimation) of 3 would suit most cases.

In relation to surface finish properties, Mills and Redford (1983) pointed out that in many metal removal operations roughness values would depend on the direction of measurement, where the surface finish in the direction of tool feed is usually poorer than that in a direction perpendicular to it. Thus, for most metal cutting operations it is recommended to measure surface finish in the direction in which the poorest surface finish is expected. The machine performs cuts *along* the workpiece leaving lays in that direction (Fig. 3.6). Therefore, in this case, it is expected to find poorer surface finish if the roughness is measured *across* the workpiece. This means two data sets, or subsets, are going to be obtained: the parallel data set (measuring roughness along the direction of cut) and the perpendicular data set (measuring roughness across the direction of cut). Special care was taken when positioning the workpiece under the probe stylus (Fig. 3.7) so the angle formed by lay direction and probe travel direction was approximately 0° (parallel data set) or 90° (perpendicular data set). During milling, it is possible to get debris, bumps, etc, on the workpiece surface which increase surface roughness, thereby causing variation. For this reason, measurements were made on three different points of each of the eight workpiece areas (Fig. 3.8) and these values were averaged.

Data analysis was eased through the organisation and classification of these measurements (data) into two separate stages. The first stage involved the utilisation of the two data sets generated from both measurement methods (parallel and perpendicular to direction of cut) to serve two purposes: firstly to compare the effectiveness of the two measurement methods for estimating factor/level significance and secondly to estimate the importance of choosing the right number of repetitions for an experiment in variance control (studied thoroughly in Section 6.3). This first stage was carried out with the data of the first block of the full factorial array. The outcome of this first stage influenced the choice of these two elements (measurement method and number of repetitions) for the next stage. The second stage, which makes use of the data coming from the second block of the full factorial array, featured the number of repetitions suggested in that first stage (four repetitions) with measurements made using the perpendicular method. However, no other analyses were done to these data (second block), as its main purpose was to complete the remaining part of the full factorial array. The full factorial array for the complete data set was built with data from these two blocks which will consider only four repetitions.

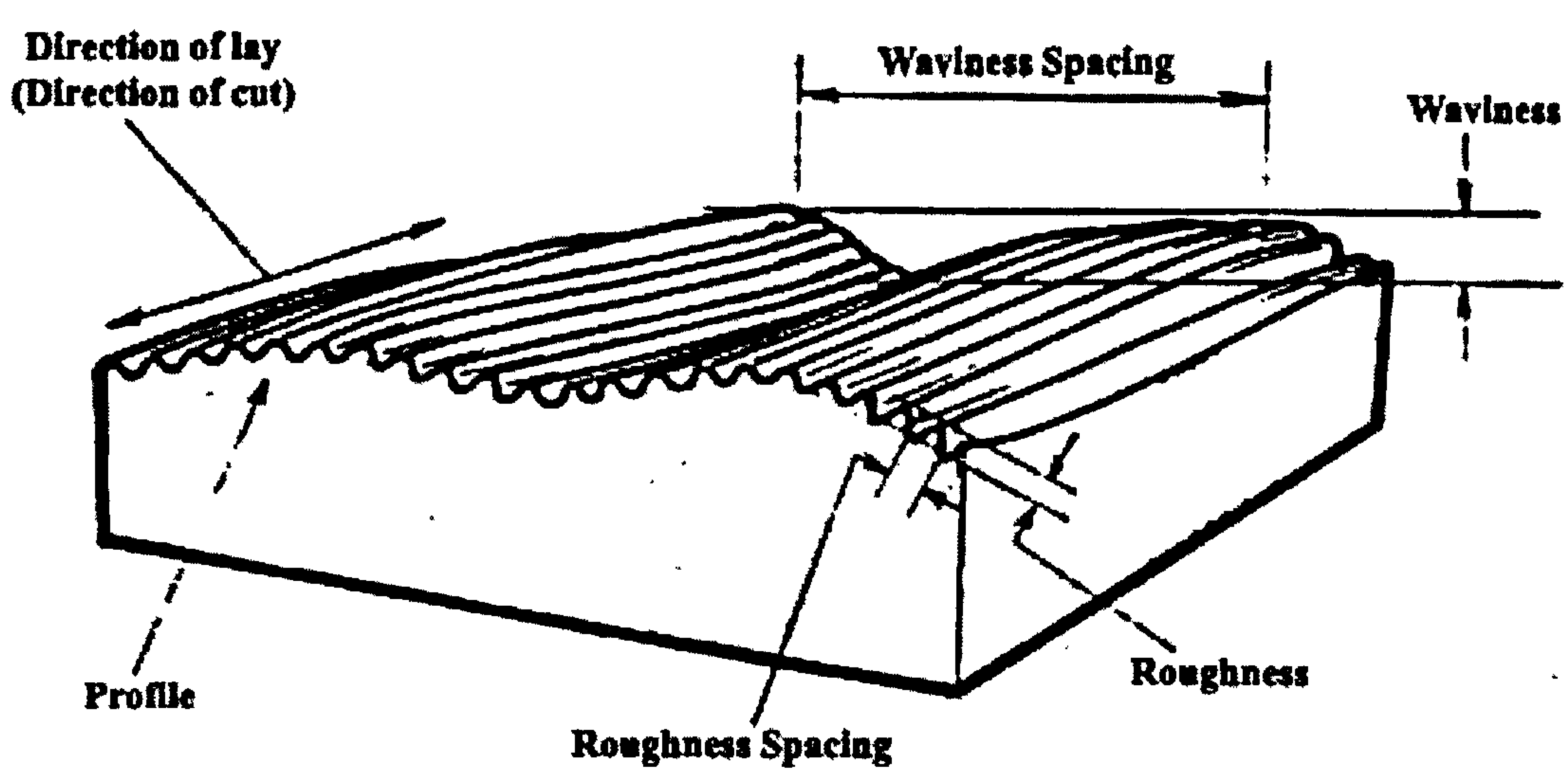


Fig. 3.6 Detail of surface profile on workpiece (BS 1134, 1990).

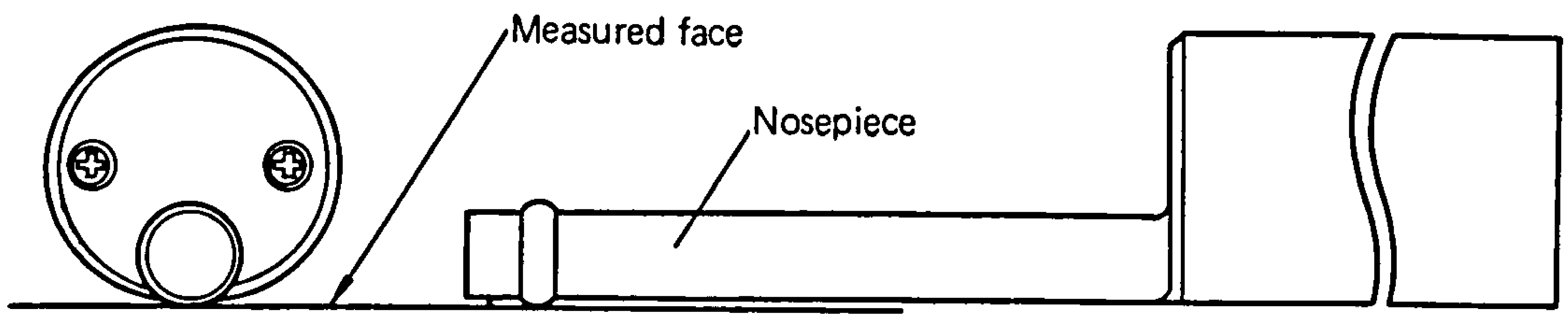


Fig. 3.7 Suggested detector positioning on sample (Mitutoyo, 1989).

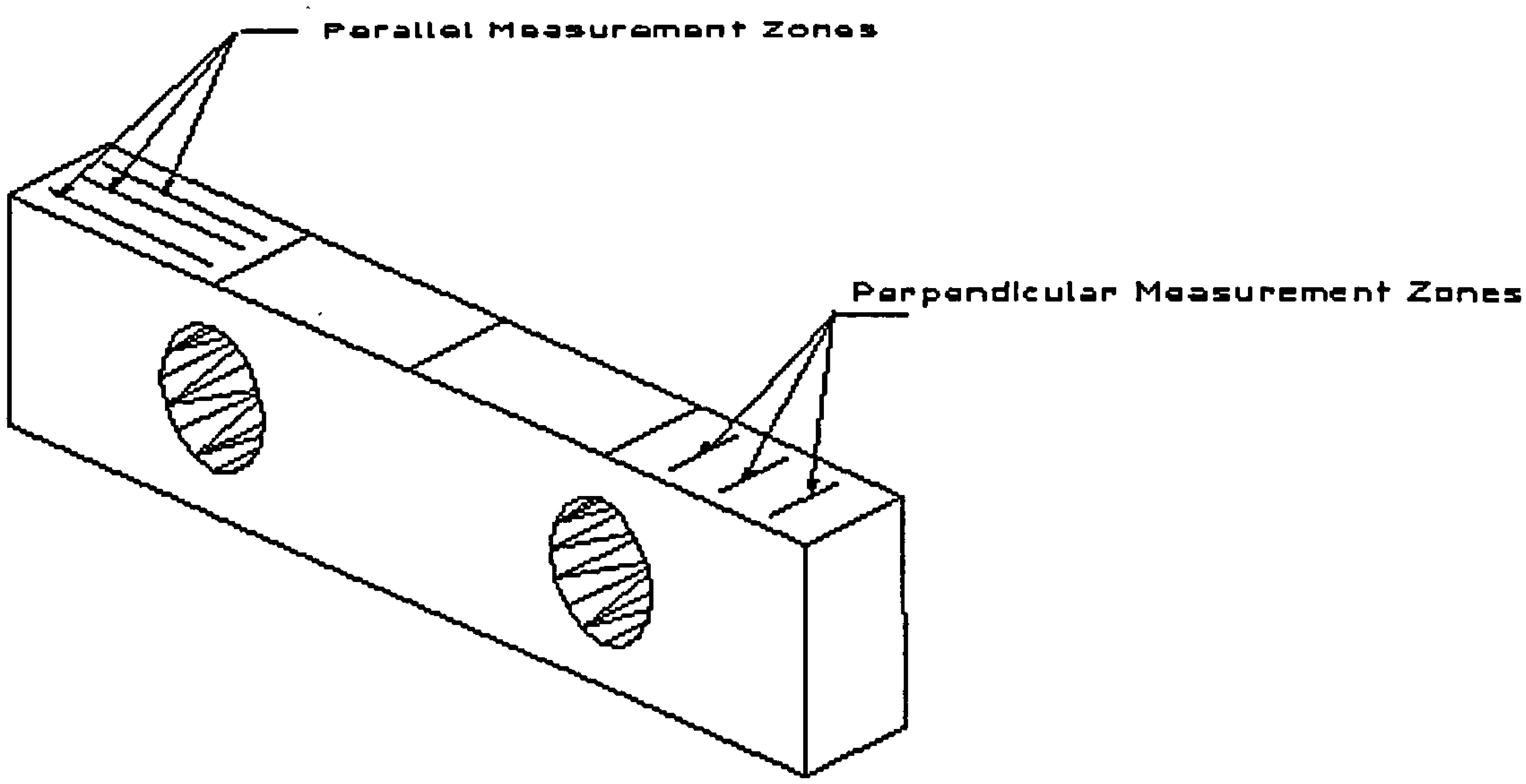


Fig. 3.8 Workpiece measurement points.

3.4.3 Data analysis

There was no need for special data arrangements so data analysis was straightforward. Similar methodology for data analysis (a series of statistical tests, mostly conventional statistical tools) was applied to both analysis stages (comparison of measurement methods and the factor/level analysis for the metal cutting experiment). A Generalised Linear Model (GLM) was preferred above conventional ANOVA tests because of its adaptability and suitability to a particular model and population being studied (Garzon, 1997). Model choice is software dependent. Whilst SAS (SAS Institute, 1991) does the whole process automatically, other programs, such as Minitab (Minitab, 1998), require user interaction for choosing factors, degree of interaction, etc. In this case, SAS software offers convenience because standard models are required, otherwise Minitab can be used for particular situations. SAS has room for particular/special models but some programming is required beforehand. The main metrics used in this case study were mean and standard deviation as measures of location and dispersion, respectively (Taher, 1995). Comparisons between both array types (Full factorial and Taguchi) were done through both stages of this case study, using identical analysis procedures and metrics. Mean, standard deviation and Taguchi's Signal-to-Noise ratio (SNR) (precisely, Smaller-The-Better) were calculated on each run from roughness values obtained considering the whole eight repetitions in this block. For calculation purposes, in both experimental arrays (full factorial and Taguchi L_{16}) roughness mean, standard deviation and SNR have been treated as *responses* in order to study surface roughness location and dispersion behaviours.

Data for the Taguchi L_{16} array were extracted from the full factorial data set. Taher (1995) demonstrated that there are no big differences in the final evaluation of both array types, especially for responses such as surface finish in which variation among different runs is not considerable. It is also assumed that any considerable and/or particular variation can be assumed as part of the variability of a normal manufacturing process, which is intended to be simulated here. For this reason, it has been assumed that data extraction from the full factorial array, to be used as original data generated for the Taguchi array, should not affect the final outcome.

3.4.3.1 Measurement methods comparison

The analysis has been sequentially organised to investigate significant main factors and two-factor interactions. Preliminary exploration of the perpendicular data set for the full factorial and Taguchi arrays (Appendixes B1 and B2, respectively), as well as parallel data set (Appendix B3 and B4, respectively), with an initial analysis of the response through an Analysis of Variance (ANOVA) test including main factor and interaction effects, was carried out to determine model validity (Tables 3.3 and 3.4). It can be seen that the model fitting for the three responses of both data sets (parallel and perpendicular) was achieved with a high degree of confidence for main effects and interactions of the full factorial array (ie mean response: $p > F = 0.000$ with 63 degrees of freedom in total). Unfortunately it was not the case for the model validity test for the Taguchi array (Table 3.4) which was affected by possible high levels of confounding within the design. It is important to point out that unless this fitting test shows appropriate values ($p > F$ equal to or lower than 0.005) further tests based on the fitted model would be considered questionable. Also, when sequential sums of squares (Seq SS) and adjusted sums of squares (Adj SS) are the same as in Tables 3.3 and 3.4 the model does not contain covariates and is orthogonal (Minitab, 1998).

Following this, factor analysis of the full factorial array through ANOVA (featuring responses for both measurement data sets) using Adjusted SS for tests involving main factors and high-order interactions generated Table 3.5. In addition, surface finish percentage contribution of the effects (Fig. 3.15 and 3.16) was estimated based on Table 3.5. ANOVA identified four factors (coolant, direction of cut, number of cuts and depth of cut) as significant for all responses (mean, standard deviation and SNR) on both parallel and perpendicular measurement data sets. Coolant (C) has the largest effect on surface finish among the main factors for the perpendicular method (Fig. 3.15), whilst direction of cut was the most important factor for the parallel method (Fig. 3.15). Differences between these two factors were marginal and their combination may count up to two thirds of the importance of the total represented by the main factors. Surprisingly, factors that may be expected to be important, such as tool speed (TS) and workpiece speed (WS), were not significant at all in this experiment (Table 3.5 and Fig. 3.15). Certainly, selected level values (constrained by the equipment) may not be far enough apart to show significant differences. Factor significance and effect on surface finish was similar for either methods using the full factorial array (Fig. 3.15 to 3.18).

It is important to point out that within the percentage contribution of the effects interactions take up more than half of the influence on the responses. For instance, 58.39% of the effects on surface finish (mean response - full factorial array - perpendicular data set) are caused by interactions (Fig. 3.15), which certainly ratifies their importance/presence. Similar values were obtained for the parallel-data-set responses (full factorial) (Fig. 3.15). Two and three-factor interactions were studied in more detail for significance through ANOVA (Table 3.5). Among two-factor interactions, only those between the significant main factors were found significant for all responses in the full factorial array, some for both perpendicular and parallel data sets, ie between depth of cut and coolant (DC*C), depth of cut and direction of cut (DC*DIC) and others for the perpendicular data set only, ie coolant and direction of cut (C*DIC), coolant and number of cuts (C*CL) and direction of cut and number of cuts (DIC*CL) (Table 3.5). These significant interactions corroborate what has been said in the literature (Krar *et al*, 1977; Mills and Redford, 1983; Baril, 1987) regarding milling method and coolant usage, where they have been identified as very important for metal cutting processes in general (Section 3.2).

Higher order interactions, among three or more factors, are commonly dismissed, in particular by Taguchi (Peace, 1993; Ross, 1988). However, in this case two three-factor interactions were found significant for all responses in the full factorial array: depth of cut, coolant and direction of cut (DC*C*DIC) (Perpendicular method only) and coolant, direction of cut and number of cuts (C*DIC*CL) (both perpendicular and parallel methods), with the latter having the largest effect of its type. Apart from the effects found significant common to all responses, there were some of them significant for the SNR response only. ANOVA indicated that one main factor (depth of cut (DC) (F-value=38.58, p>F=0.000)), one two-factor interaction (between tool speed and coolant (TS*C) (F-value=10.2, p>F=0.004)) and two three-factor interactions (among tool speed, coolant and number of cuts (TS*C*CL) (F-value=12.34, p>F=0.002) and workpiece speed, depth of cut and coolant (WS*DC*C) (F-value=12.6, p>F=0.004)) were found significant in addition to those for mean and standard deviation responses (Table 3.5). Notice that these additional significant effects were present in the perpendicular data set only. It was observed also that some of the interactions included non-significant main factors, which may suggest the possibility that these factors may have roles that are more important if different levels were selected. It is worth mentioning that two observations for mean and

SNR responses (runs 24 and 33, Appendix B1) and three for Standard Deviation (runs 33, 34 and 56, Appendix B1), were considered by the GLM as unusual due to observations with large standardized residual. It is presumed that the presence of these unusual observations may make the distribution skewed.

On the other hand, poor model fitting (shown by Table 3.4) and the high amount of confounding spoiled the ANOVA results for the Taguchi array. However, looking at the percentage contribution of the effects (Fig. 3.16), significant factors and interactions have similar influence on the responses as was found for the full factorial array. Based on results found in this ANOVA test only, taking any decision at this point may be misleading even if used for screening purposes. For this reason, it is generally necessary to appeal to the main effect plots, which can be of help in such cases.

The traditional approach (Tables 3.7 and 3.8) for testing for the best design combination can be overshadowed at times by the graphical alternative: main effects and interactions dot-line plots. These plots offer extra functionality easing the task of determining and/or confirming influential levels for factors and their interactions, mostly in cases where factor significance is not so clear. Testing for the best may be based on limited assumptions while it is restricted to those runs contained within the Taguchi fraction and not all possible combinations. Pareto charts (Burr, 1990) complement information already obtained for factor and interaction ranking. Pareto charts for all responses (Fig. 3.17 and 3.18) showed that interactions involving the most significant factors mostly had the biggest effects followed by other important factors such as tool and workpiece speed. Pareto charts had similar trends, regarding the three responses, on charts for both measurement methods and may appear to contradict ANOVA to some extent. However, it actually means these two factors are important but level settings may not be far apart enough for ANOVA to detect significant effects. At the same time, facts like, application of blocking techniques due to difficult to set/change factors and significant factors being ranked by Pareto charts a lot lower than non-significant main and interaction effects, may be a clear indication of being actually studying a split-plot design (Grove and Davis, 1992). Despite of the amount of confounding usually present in over-saturated Taguchi designs, Pareto charts contribute with the estimation of interaction roles in the process by ranking their significance and "forcing" them to reach a minimal confidence level (usually above 90% confidence).

Based on the eight repetitions for R_a, main effect and interaction dot-line plots were evaluated for three responses (mean, standard deviation and SNR) in order to determine the best design combination. Main effect plots for mean (Fig. 3.9 and 3.10), standard deviation (Fig. 3.11 and 3.12) and Signal-to-Noise Ratio responses (Fig. 3.13 and 3.14) showed similar (or nearly identical) configuration when comparing both methods for the same response and the same design type. Even though this type of similarity may be ideal for experimenters (as it may be an easy conclusion to draw from it) this is not necessarily the case here as the factor effect estimations obtained for full factorial were sometimes different to those obtained for the Taguchi array.

The full factorial array estimation of main effect plots for mean response (Fig. 3.9) and Signal-to-Noise Ratio (Fig. 3.13) indicated a best possible combination with tool speed of 2700 rev/min., workpiece speed of 203 mm/min, depth of cut of 0.5mm, coolant on, climbing milling and only one cut per lap. Both plots (Fig. 3.9 and 3.13) also agreed with the ANOVA results indicating factors coolant, direction of cut and number of cuts as significant. The best design settings for the standard deviation response (Fig. 3.11) did not show similar patterns for both measurement methods. Specifically, the best setting with the perpendicular method proved to be identical to those suggested by the mean and SNR responses; but the settings indicated by the parallel method were similar to those of the mean response with the exception of workpiece speed factor for which the best setting was 330 mm/min. The SNR plot (Fig. 3.13) results for the best design settings proved to be the same as for the mean, reinforcing Taher's (1995) results that this correlates with the mean. To confirm this, and in order to justify similarities among results from the three responses which suggested possible correlation for these responses, correlation tests (Tables 3.9 and 3.10) were carried out prior to testing for best design combination. There was not only correlation between mean and SNR but with mean and standard deviation also.

For both Taguchi arrays (parallel and perpendicular), a best possible combination (using linear graph II (Fig. 3.3)) with tool speed of 2700 rev/min., workpiece speed of 330 mm/min, depth of cut of 1 mm, coolant on, climbing milling and only one cut per lap, was suggested by both mean and Standard Deviation responses (Fig. 3.10 and 3.12). On the other hand, the SNR response for the parallel method indicated similar settings to those found for mean and SNR for the full factorial array, a situation that changes slightly for the direction of cut factor (perpendicular method) which suggests conventional milling as best setting (Fig. 3.14). Notice that this combination (mean and SNR) was the same best setting suggested by the full factorial design but is not included within the Taguchi design. Analogously, the best design combination was also studied for linear graph IV recommending a different combination with tool speed of 3200 rev/min and depth of cut of 0.5 mm.

Two-factor interaction dot-line plots were also evaluated for the full factorial array on both measurement data sets. As happened with the main factor plots, interaction dot-line plots (Fig. 3.19 to 3.24) showed similar (or nearly identical) configuration when comparing both methods for the same response and the same design type, obviously with some minor variations but keeping more or less the same tendency. They did not show more relevant information than already found with the ANOVA test. Nonetheless, there were some interesting interactions between tool speed and depth of cut (mean and SNR responses) and between tool speed and workpiece speed (SNR response) not seen on previous ANOVA tests, which reinforces the presumption for tool and workpiece speed of having more significant roles. Values were too close to each other in some plots, mostly for those with the parallel method, to make proper comparisons from two-factor interaction dot-line plots. However, this closeness of values obtained for this change in measurement method can be numerically better appreciated in the least-squares method calculations (Tables 3.7 and 3.8).

As suggested by Taguchi (1987), confirmation runs for Taguchi arrays were carried out using the best design settings obtained from both linear graphs (Table 3.11). The results were quite similar, though a small difference could be appreciated between results obtained for both linear graphs, with settings from linear graph II being (slightly) the better estimation for both location and dispersion. Equivalent runs in the original full factorial to these confirmation runs for linear graphs II and IV were 23 and 57 respectively (in the perpendicular data set: Appendix B1). When these confirmation runs were compared to their equivalent from the full factorial, results obtained with the confirmation run (Linear Graph II) were 20.3% (mean), 84.6% (standard deviation) and 3200% (SNR) off the full factorial values. For the linear graph IV was slightly worst with 28.9% (mean), 350% (standard deviation) and 3500% (SNR) off the full factorial values. This gap indicates that, apart from both linear graphs performing closely to each other, there is a performance gap between them and their equivalent full factorial runs, which may be caused in part by the effect of repetitions.

		Source	DF	Seq SS	Adj SS	Adj MS	F	p>F
Mean	Perpendicular	Main Effects	6	756.33	756.33	126.05	42.86	0
		2-Way Interactions	15	752.98	752.98	50.20	17.07	0
		3-Way Interactions	20	308.41	308.41	15.42	5.24	0
		Residual Error	22	64.71	64.71	2.94		
		Total	63	1882.43				
	Parallel	Main Effects	6	888.3	888.3	148.05	23.57	0
		2-Way Interactions	15	888.6	888.6	59.24	9.43	0
		3-Way Interactions	20	382.4	382.4	19.12	3.04	0.006
		Residual Error	22	138.2	138.2	6.28		
		Total	63	2297.4				
Std. Dev.	Perpendicular	Main Effects	6	92.90	92.90	15.48	25.50	0
		2-Way Interactions	15	93.14	93.14	6.21	10.23	0
		3-Way Interactions	20	42.23	42.23	2.11	3.48	0.003
		Residual Error	22	13.36	13.36	0.61		
		Total	63	241.63				
	Parallel	Main Effects	6	43.71	43.71	7.29	20.56	0
		2-Way Interactions	15	41.19	41.19	2.75	7.75	0
		3-Way Interactions	20	18.00	18.00	0.90	2.54	0.018
		Residual Error	22	7.80	7.80	0.35		
		Total	63	110.70				
STB	Perpendicular	Main Effects	6	756.33	756.33	126.05	42.86	0
		2-Way Interactions	15	752.98	752.98	50.20	17.07	0
		3-Way Interactions	20	308.41	308.41	15.42	5.24	0
		Residual Error	22	64.71	64.71	2.94		
		Total	63	1882.43				
	Parallel	Main Effects	6	5251.6	5251.6	875.26	118.43	0
		2-Way Interactions	15	3197.8	3197.8	213.19	28.85	0
		3-Way Interactions	20	502.5	502.5	25.13	3.4	0.003
		Residual Error	22	162.6	162.6	7.39		
		Total	63	9114.5				

Table 3.3 ANOVA model fitting test for the full factorial array (measurement method comparison based on data from appendixes B1 and B3).

		Source	DF	Seq SS	Adj SS	Adj MS	F	p>F
Mean	Perpendicular	Main Effects	6	208.72	208.72	34.79	1.22	0.472
		2-Way Interactions	6	193.06	193.06	32.18	1.13	0.5
		Residual Error	3	85.6	85.6	28.53		
		Total	15	487.38				
	Parallel	Main Effects	6	142.17	142.17	23.69	1.36	0.433
		2-Way Interactions	6	129.79	129.79	21.63	1.24	0.466
		Residual Error	3	52.45	52.45	17.48		
		Total	15	324.41				
Std. Dev.	Perpendicular	Main Effects	6	37.98	37.98	6.33	1.24	0.466
		2-Way Interactions	6	33.91	33.91	5.652	1.11	0.507
		Residual Error	3	15.32	15.32	5.106		
		Total	15	87.21				
	Parallel	Main Effects	6	14.548	14.548	2.425	1.32	0.442
		2-Way Interactions	6	12.988	12.988	2.165	1.18	0.484
		Residual Error	3	5.504	5.504	1.835		
		Total	15	33.04				
STB	Perpendicular	Main Effects	6	495.8	495.8	82.64	2.29	0.266
		2-Way Interactions	6	364.3	364.3	60.72	1.68	0.359
		Residual Error	3	108.5	108.5	36.16		
		Total	15	968.6				
	Parallel	Main Effects	6	983.2	983.2	163.87	3.42	0.17
		2-Way Interactions	6	650.6	650.6	108.44	2.26	0.269
		Residual Error	3	143.9	143.9	47.97		
		Total	15	1777.8				

Table 3.4 ANOVA model fitting test for the Taguchi array (measurement method comparison based on data from appendixes B2 and B4).

		Perpendicular method						Parallel method					
		Mean		Std. Dev.		STB		Mean		Std. Dev.		STB	
Source	DF	F	p>F	F	p>F	F	p>F	F	p>F	F	p>F	F	p>F
TS	1	2.02	0.17	0.25	0.62	2.50	0.128	0.16	0.692	2.52	0.127	0.64	0.431
WS	1	0.81	0.377	1.53	0.23	0.76	0.393	0.55	0.467	0.40	0.531	0.08	0.78
DC	1	12.31	0.002	10.49	0.004	38.58	0.000	5.96	0.023	6.50	0.018	10.56	0.004
C	1	93.3	0.000	54.41	0.000	1266.27	0.000	49.05	0.000	45.91	0.000	281.71	0.000
DIC	1	86.37	0.000	53.84	0.000	883.49	0.000	50.7	0.000	46.33	0.000	384.74	0.000
CL	1	62.33	0.000	32.5	0.000	329.17	0.000	35.03	0.000	21.69	0.000	32.86	0.000
TS*WS	1	0.5	0.488	0.01	0.921	2.90	0.103	0.66	0.424	0.43	0.52	5.19	0.033
TS*DC	1	0.63	0.435	0.7	0.412	2.00	0.171	2.18	0.154	0.99	0.329	1.16	0.293
TS*C	1	2.31	0.143	0.19	0.666	10.2	0.004	0.18	0.676	2.34	0.141	2.02	0.169
TS*DIC	1	1.97	0.174	0.18	0.676	1.75	0.199	0.15	0.70	2.61	0.121	0.07	0.796
TS*CL	1	2.63	0.119	0.00	0.955	8.99	0.007	0.18	0.677	1.9	0.182	0.1	0.75
WS*DC	1	1.38	0.252	2.82	0.108	0.38	0.543	0.18	0.672	2.19	0.153	0.92	0.349
WS*C	1	0.76	0.394	1.51	0.232	0.15	0.702	0.56	0.462	0.46	0.504	0.07	0.795
WS*DIC	1	0.73	0.403	1.74	0.200	0.03	0.857	0.58	0.455	0.3	0.588	0.42	0.526
WS*CL	1	0.81	0.377	2.26	0.147	2.63	0.119	0.49	0.491	0.18	0.677	0.11	0.744
DC*C	1	13.01	0.002	10.63	0.004	60.46	0.000	5.6	0.027	5.79	0.025	3.03	0.096
DC*DIC	1	13.26	0.001	10.61	0.004	67.32	0.000	5.82	0.025	6.32	0.02	6.93	0.015
DC*CL	1	6.05	0.022	4.8	0.039	2.37	0.138	4.12	0.055	1.93	0.178	0.77	0.389
C*DIC	1	90.6	0.000	53.88	0.000	1120.3	0.000	49.28	0.000	44.06	0.000	291.76	0.000
C*CL	1	61.8	0.000	32.83	0.000	313.21	0.000	36.6	0.000	24.37	0.000	83.56	0.000
DIC*CL	1	59.56	0.000	31.27	0.000	239.55	0.000	34.91	0.000	22.38	0.000	36.6	0.000
TS*WS*DC	1	0.8	0.381	0.34	0.566	0.72	0.405	0.87	0.362	0.1	0.753	0.2	0.659
TS*WS*C	1	0.47	0.499	0.01	0.938	2.39	0.137	0.55	0.466	0.59	0.452	0	0.989
TS*WS*DIC	1	0.34	0.564	0.02	0.891	0	0.998	0.49	0.489	0.67	0.421	1.38	0.253
TS*WS*CL	1	0.14	0.712	0	0.954	0.72	0.406	0.37	0.55	1.67	0.21	0.03	0.855
TS*DC*C	1	0.76	0.392	0.68	0.420	6.69	0.017	2.22	0.151	0.76	0.391	2.46	0.131
TS*DC*DIC	1	0.73	0.401	0.62	0.441	6.06	0.022	2.07	0.164	1.02	0.323	0.11	0.739
TS*DC*CL	1	0.45	0.510	0.96	0.338	2.22	0.151	2.15	0.157	0.71	0.408	2.73	0.113
TS*C*DIC	1	2.16	0.156	0.16	0.695	6.5	0.018	0.14	0.71	2.19	0.153	0.14	0.709
TS*C*CL	1	2.73	0.113	0.01	0.935	12.34	0.002	0.19	0.67	2.5	0.128	1.28	0.27
TS*DIC*CL	1	2.41	0.135	0.00	0.969	4.23	0.052	0.17	0.681	1.82	0.191	0.05	0.831
WS*DC*C	1	1.84	0.189	2.93	0.101	12.6	0.002	0.27	0.607	1.72	0.203	1.38	0.253
WS*DC*DIC	1	1.44	0.243	2.63	0.119	1.08	0.31	0.2	0.659	2.03	0.168	0.51	0.483
WS*DC*CL	1	1.14	0.298	2.52	0.127	0.35	0.561	0.22	0.641	1.78	0.196	0.03	0.857
WS*C*DIC	1	0.69	0.416	1.65	0.213	0.1	0.757	0.56	0.461	0.35	0.563	0.01	0.933
WS*C*CL	1	0.61	0.444	2.16	0.156	0.19	0.671	0.48	0.494	0.25	0.62	0.15	0.703
WS*DIC*CL	1	0.81	0.378	2.38	0.138	2.26	0.147	0.6	0.446	0.17	0.685	2.5	0.128
DC*C*DIC	1	12.7	0.002	10.79	0.003	49.46	0.000	5.55	0.028	5.98	0.023	1.94	0.178
DC*C*CL	1	6.51	0.018	4.79	0.040	0.01	0.924	4.15	0.054	2.19	0.153	0.8	0.382
DC*DIC*CL	1	6.88	0.016	5.05	0.035	0.63	0.437	3.83	0.063	1.58	0.223	1.51	0.232
C*DIC*CL	1	61.25	0.000	31.89	0.000	295.66	0.000	35.79	0.000	22.71	0	50.79	0.000
Error	22	64.71		13.36		19.07		138.165		7.7955		162.59	
Total	63	1882.43		241.63		4142.52		2297.432		110.6933		9114.5	

Table 3.5 ANOVA using Adjusted SS for Tests for the full factorial array (measurement method comparison based on data from appendixes B1 and B3).

		Perpendicular method						Parallel method					
		Mean		Std. Dev.		STB		Mean		Std. Dev.		STB	
Source	**DF**	**F**	**p>F**	**F**	**p>F**	**F**	**p>F**	**F**	**p>F**	**F**	**p>F**	**F**	**p>F**
C	1	2.13	0.24	2.19	0.235	6.71	0.081	2.48	0.214	2.53	0.21	9.42	0.055
DIC	1	1.95	0.257	2.12	0.241	4.51	0.124	2.53	0.21	2.41	0.219	9.62	0.053
CL	1	1.48	0.311	1.5	0.308	1.91	0.261	1.66	0.288	1.46	0.314	0.85	0.424
WS	1	0.48	0.538	0.43	0.559	0	0.997	0.43	0.559	0.4	0.573	0.01	0.925
TS	1	0.51	0.526	0.5	0.529	0.02	0.89	0.41	0.568	0.4	0.573	0.03	0.876
DC	1	0.76	0.448	0.69	0.466	0.57	0.507	0.63	0.485	0.74	0.454	0.57	0.507
C*DIC	1	2.06	0.247	2.09	0.244	5.84	0.094	2.46	0.215	2.46	0.215	8.81	0.059
C*CL	1	1.53	0.305	1.55	0.301	2.31	0.226	1.84	0.268	1.69	0.285	3.63	0.153
DIC*CL	1	1.43	0.318	1.4	0.322	1.52	0.305	0.43	0.56	0.38	0.582	0.01	0.924
C*WS	1	0.51	0.528	0.42	0.561	0.02	0.899	0.49	0.534	0.38	0.58	0.31	0.614
C*TS	1	0.54	0.515	0.48	0.539	0.09	0.779	0.57	0.506	0.66	0.476	0.04	0.846
C*DC	1	0.71	0.462	0.7	0.465	0.29	0.628	1.64	0.291	1.51	0.307	0.76	0.447
Error	3	85.6		15.319		108.47		52.45		5.504		143.91	
Total	15	487.38		87.209		968.65		324.41		33.04		1777.76	

Table 3.6 ANOVA using Adjusted SS for Tests for the Taguchi array (measurement method comparison based on data from appendixes B2 and B4).

		Perpendicular set			Parallel set		
Factor	**Level**	**Mean**	**Std. Dev.**	**SNR (STB)**	**Mean**	**Std. Dev.**	**SNR (STB)**
Tool speed (rev/min) (TS)	3200	3.35	0.82	-4.03	2.65	0.70	3.85
	2700	2.74	0.72	-3.66	2.40	0.46	4.39
Workpiece speed (mm/min) (WS)	203	2.85	0.65	-3.74	2.29	0.63	4.22
	330	3.23	0.89	-3.95	2.76	0.53	4.02
Depth of cut (mm) (DC)	1	3.79	1.08	-4.57	3.29	0.77	3.02
	0.5	2.29	0.45	-3.12	1.76	0.39	5.22
Coolant (C)	Off	5.12	1.49	-7.99	4.72	1.08	-1.58
	On	0.97	0.05	0.30	0.33	0.07	9.82
Direction of cut (DIC)	Climb	1.05	0.05	-0.39	0.29	0.07	10.78
	Conventional	5.03	1.48	-7.31	4.75	1.08	-2.55
Number of cuts (CL)	1	1.35	0.21	-1.73	0.67	0.23	6.07
	2	4.73	1.32	-5.96	4.38	0.93	2.17

Table 3.7 Summary table for the main-overall location and dispersion effects for parallel and perpendicular data sets-Full factorial (original data from appendixes B1 and B3)

Factor	Level	Perpendicular set Mean	Std. Dev.	SNR (STB)	Parallel set Mean	Std. Dev.	SNR (STB)
Tool speed (rev/min) (TS)	3200	3.89	1.29	-3.97	2.68	0.83	3.98
	2700	1.98	0.49	-3.51	1.34	0.40	3.39
Workpiece speed (mm/min) (WS)	203	2.01	0.52	-3.73	1.32	0.40	3.86
	330	3.86	1.26	-3.75	2.69	0.83	3.51
Depth of cut (mm) (DC)	1	4.10	1.36	-4.87	2.84	0.91	2.38
	0.5	1.77	0.42	-2.61	1.18	0.33	4.99
Coolant (C)	Off	4.88	1.73	-7.64	3.65	1.12	-1.63
	On	0.98	0.05	0.16	0.36	0.08	9.00
Direction of cut (DIC)	Climb	1.07	0.07	-0.55	0.35	0.09	9.06
	Conventional	4.80	1.71	-6.93	3.67	1.14	-1.69
Number of cuts (CL)	1	1.31	0.20	-1.67	0.66	0.21	5.29
	2	4.56	1.58	-5.82	3.36	1.03	2.09

Table 3.8 Summary table for the main-overall location and dispersion effects for parallel and perpendicular data sets-Taguchi LG II (original data from appendixes B2 and B4)

	Perpendicular set		Parallel set	
	Mean	Standard Deviation	Mean	Standard Deviation
Standard Deviation	0.961		0.793	
Smaller-The-Better	-0.937	-0.902	-0.873	-0.832

Table 3.9 Response correlations (Pearson) for full factorial array.

	Perpendicular set		Parallel set	
	Mean	Standard Deviation	Mean	Standard Deviation
Standard Deviation	1.000		0.999	
Smaller-The-Better	-0.925	-0.933	-0.888	-0.889

Table 3.10 Response correlations (Pearson) for Taguchi array.

	Factors						Roughness		
Test	TS	WS	DC	C	DIC	CL	AVG	STD	STB
LG IV	3200	330	0.5	On	Climb	1	1.280	0.099	-2.215
FF (run 57)	3200	330	0.5	on	Climb	1	0.993	0.022	0.064
LG II	2700	203	0.5	On	Climb	1	1.193	0.096	-2.026
FF (run 24)	2700	203	0.5	on	Climb	1	0.992	0.052	0.065

Table 3.11 Confirmation runs (Taguchi array).

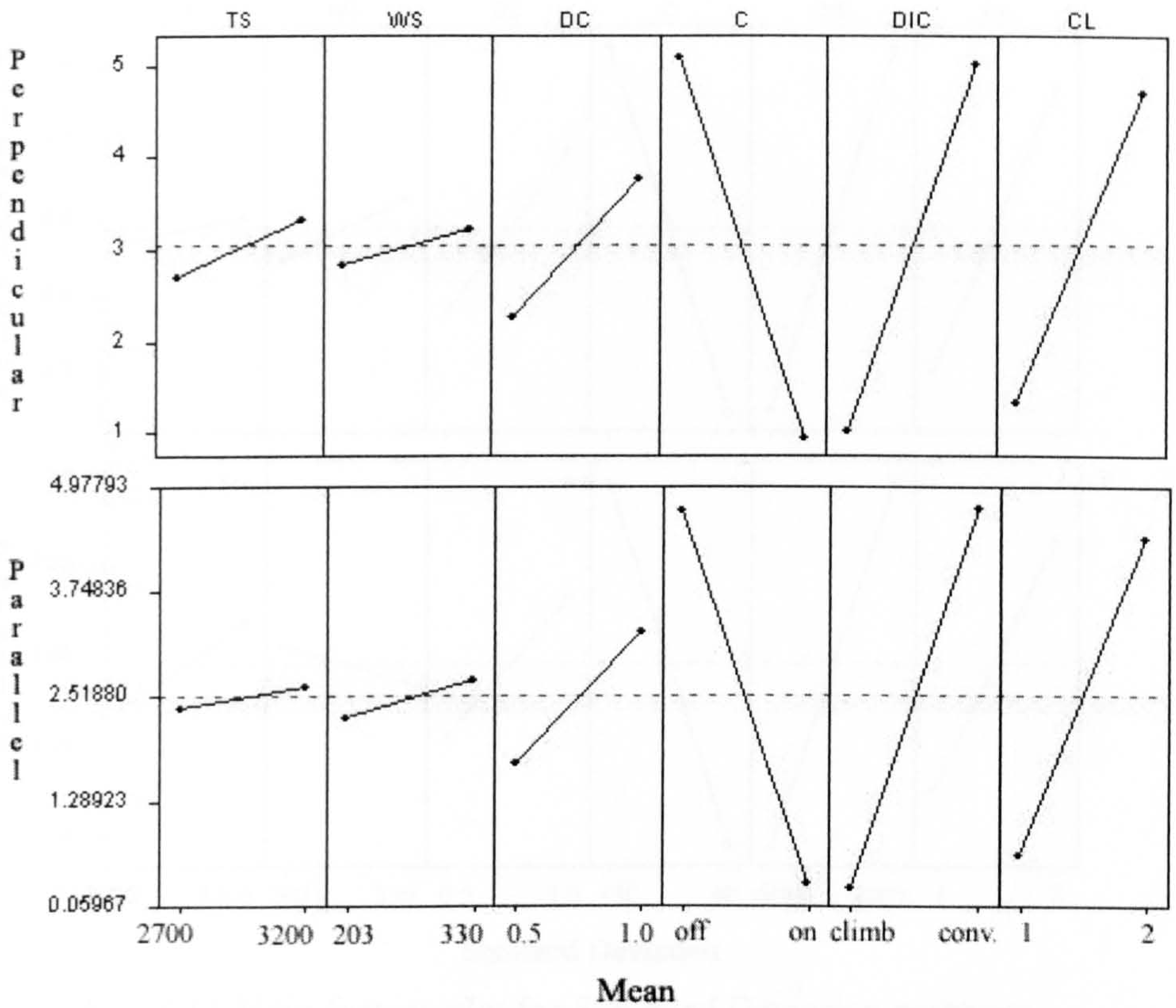


Fig. 3.9 Main factors plot for mean response (Full factorial array)

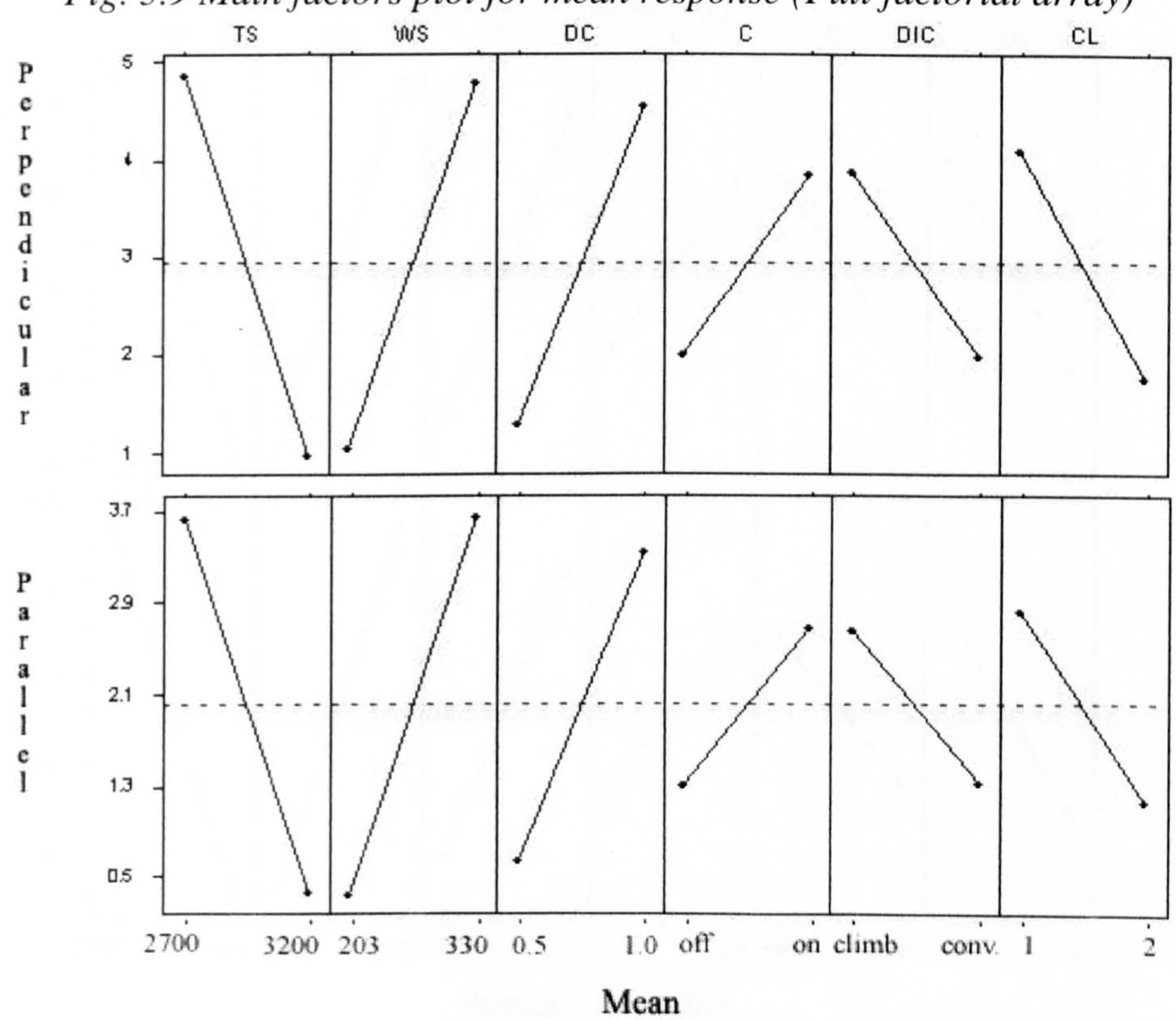


Fig. 3.10 Main factors plot for mean response (Taguchi array)

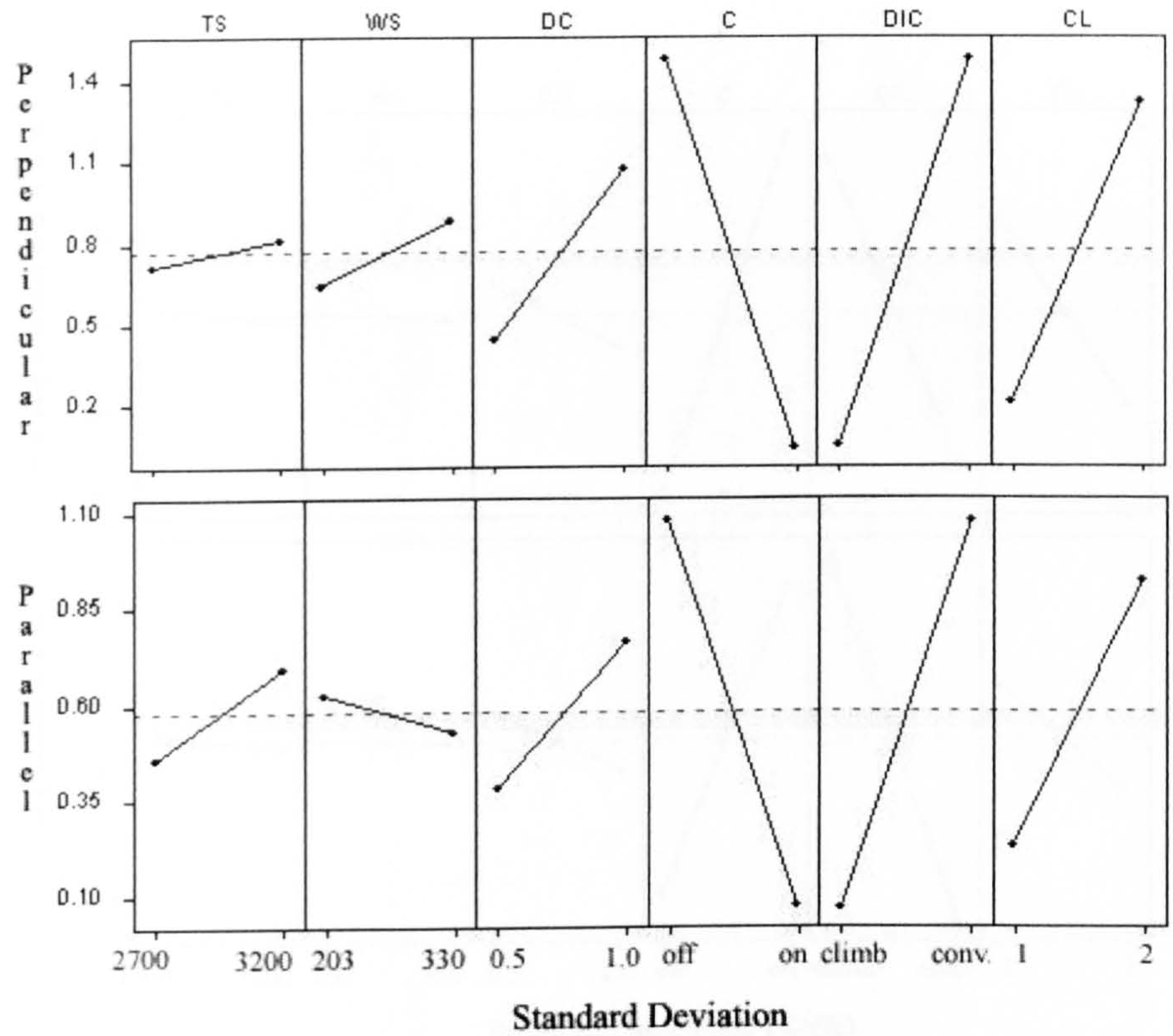


Fig. 3.11 Main factors plot for Standard Deviation response (Full factorial array)

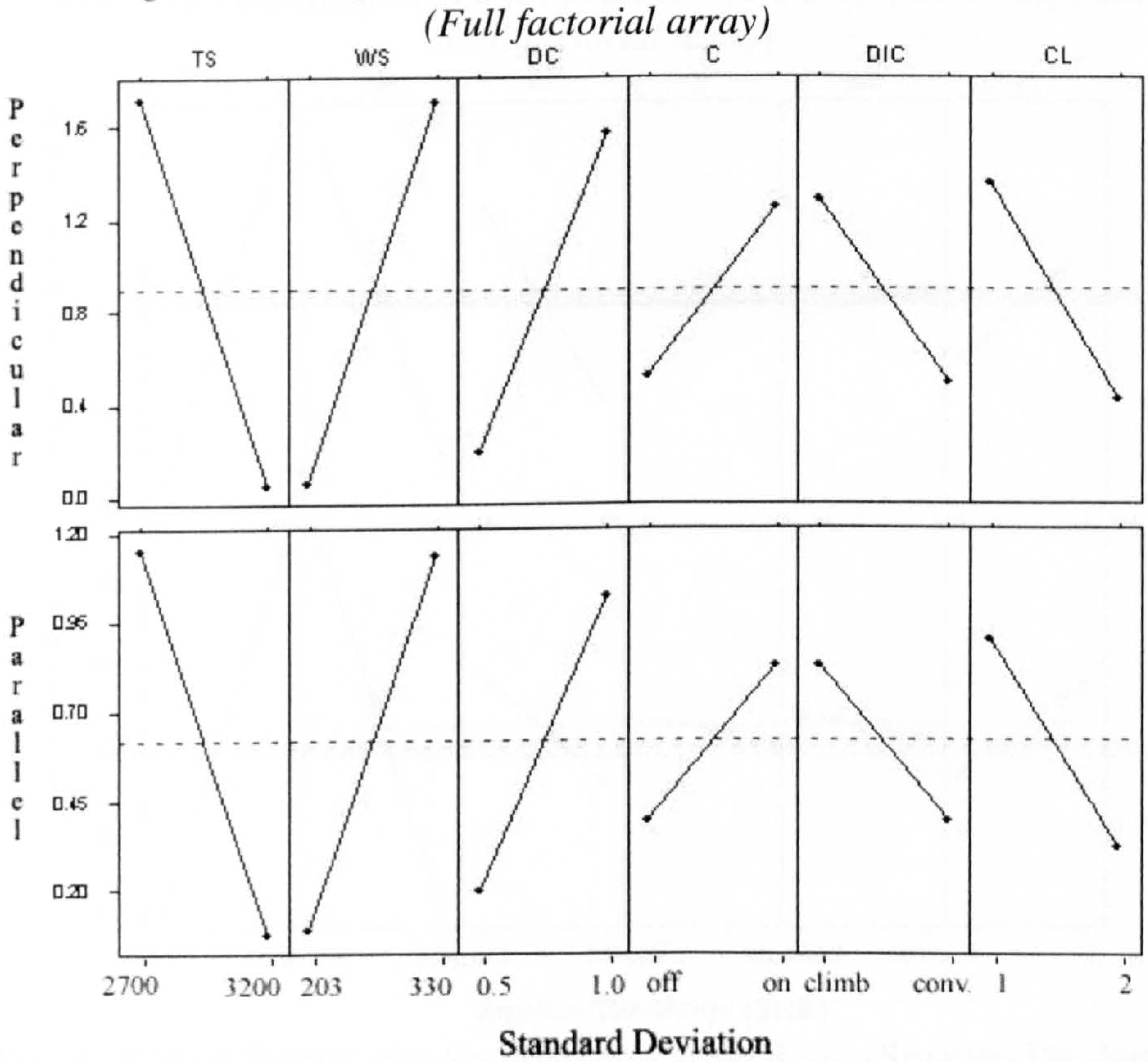


Fig. 3.12 Main factors plot for Standard Deviation response (Taguchi array)

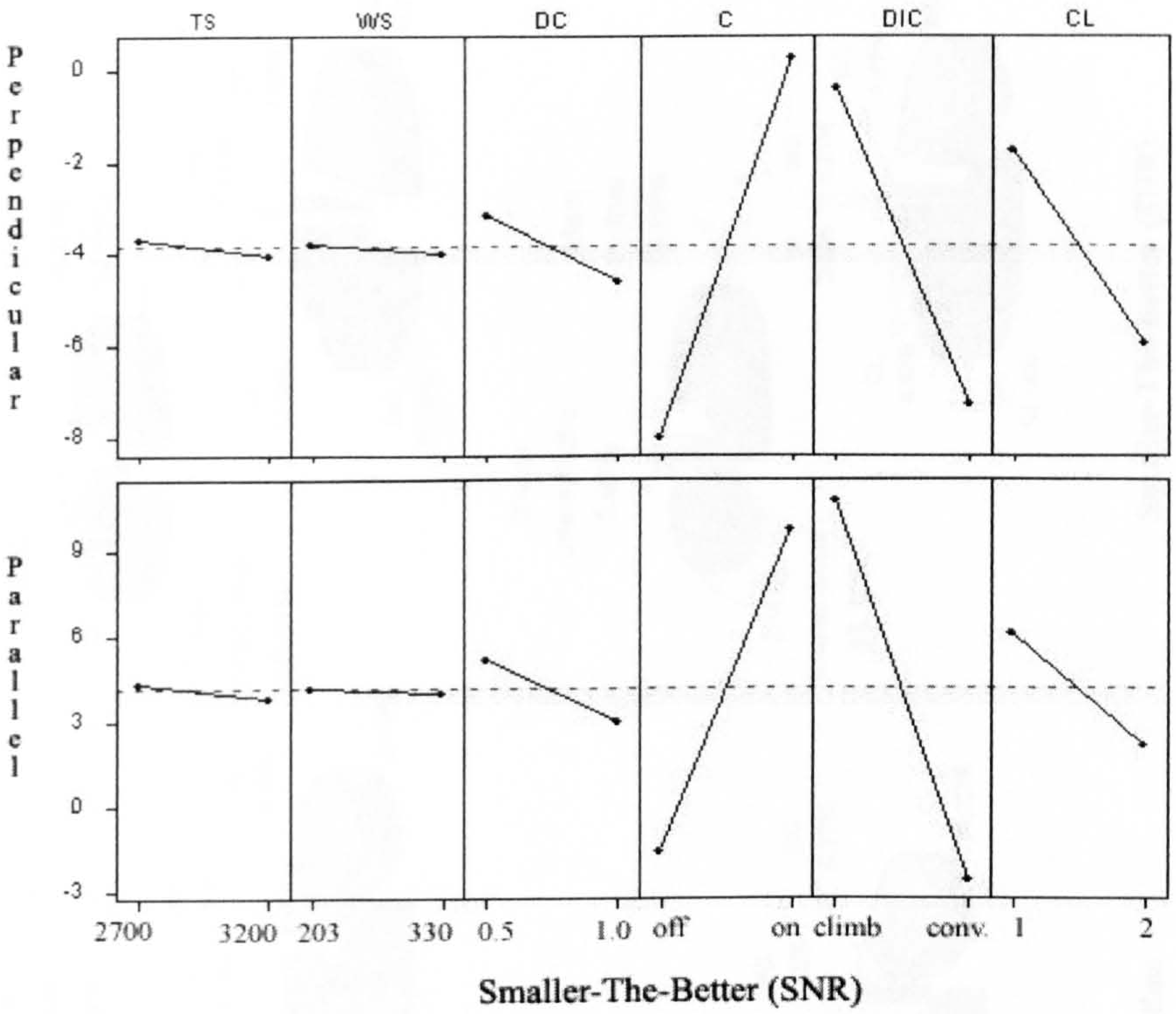


Fig. 3.13 Main factors plot for Smaller-The-Better (SNR) response (Full factorial array)

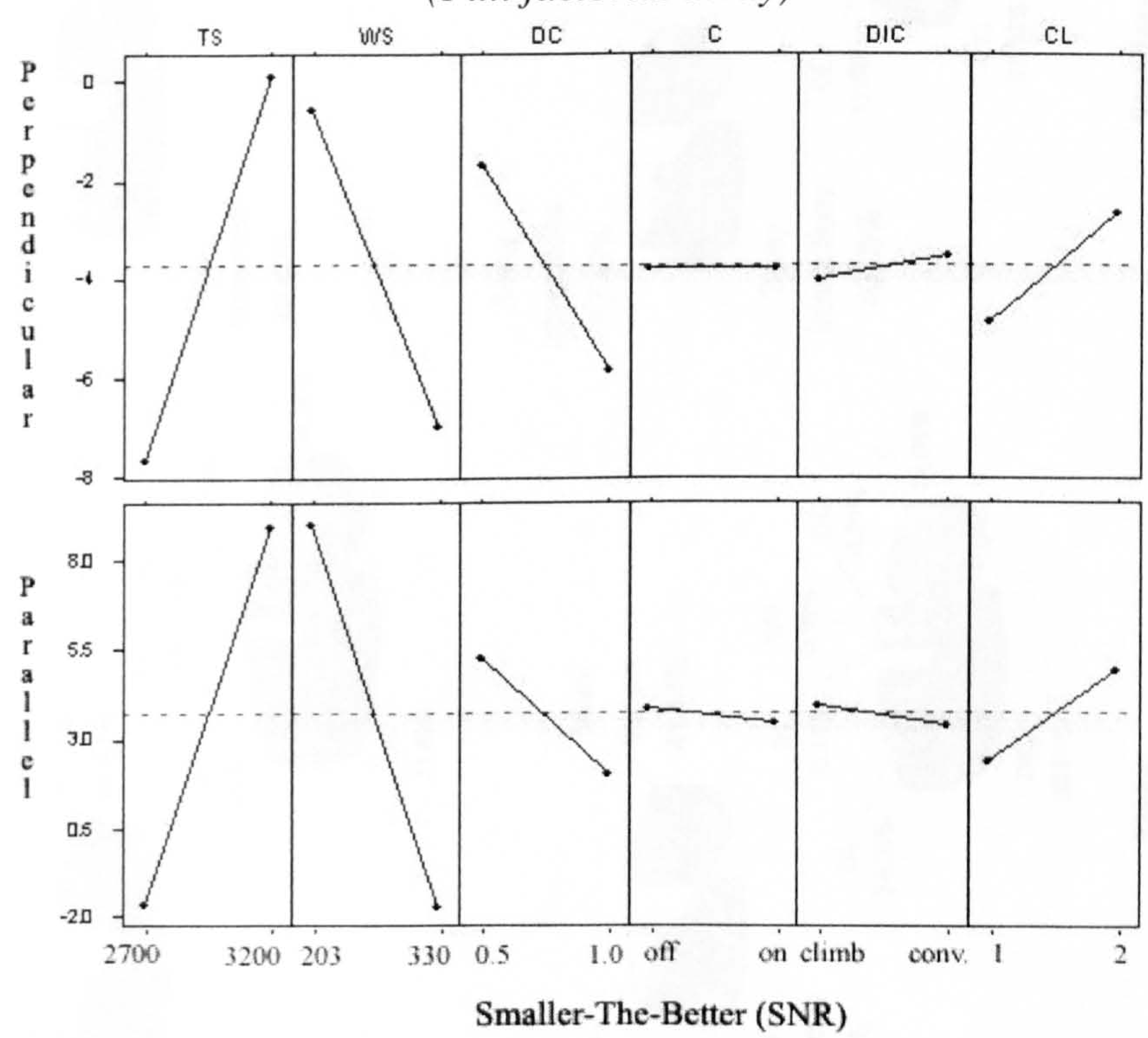


Fig. 3.14 Main factors plot for Signal-to-Noise Ratio (Smaller-The-Better) *response (Taguchi array)*

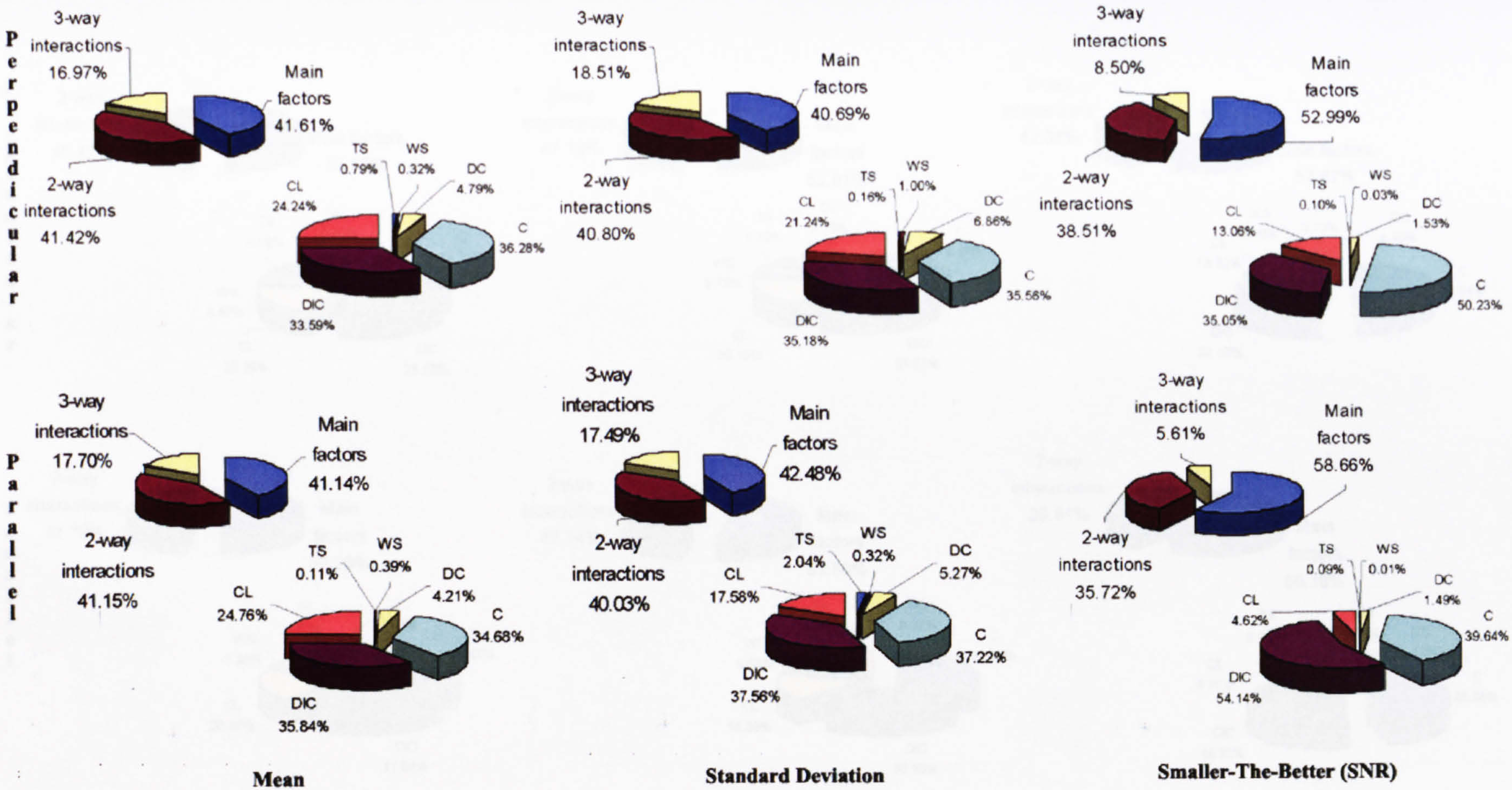


Fig. 3.15 Surface finish percentage contribution of the effects (full factorial array).

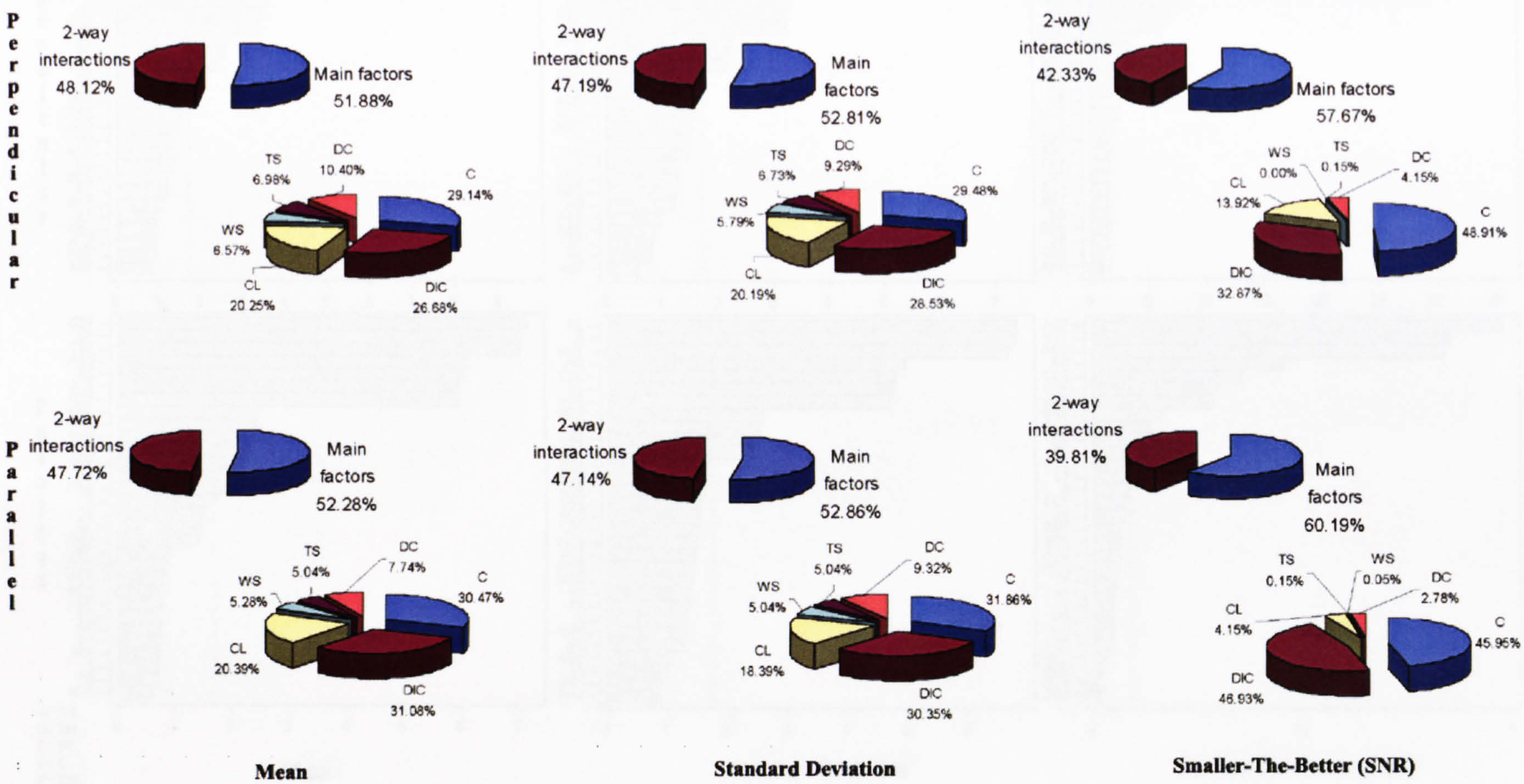


Fig. 3.16 Surface finish percentage contribution of the effects (Taguchi array).

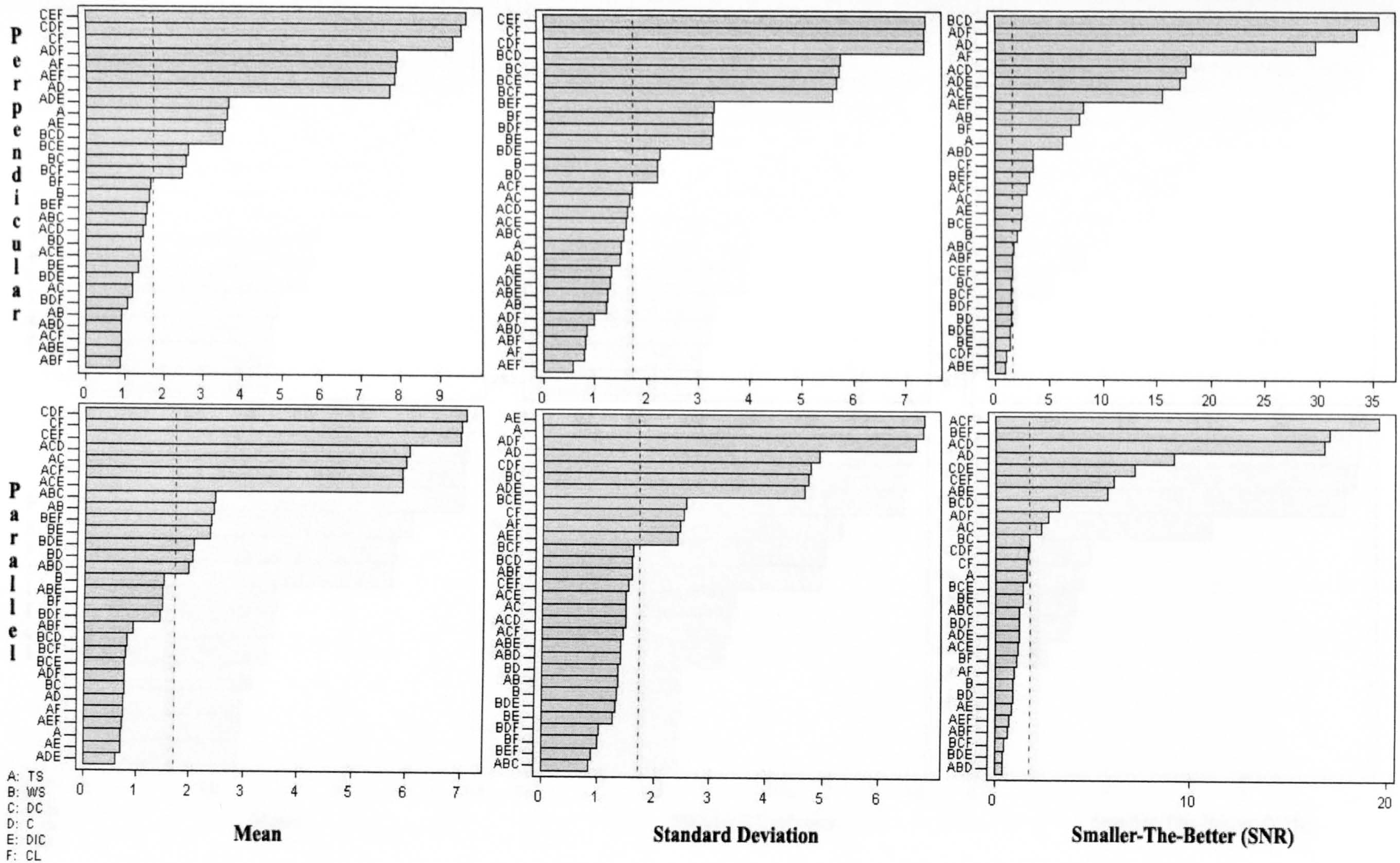


Fig. 3.17 Summary of Pareto charts of the standardised effects (full factorial. Alpha=0.10)

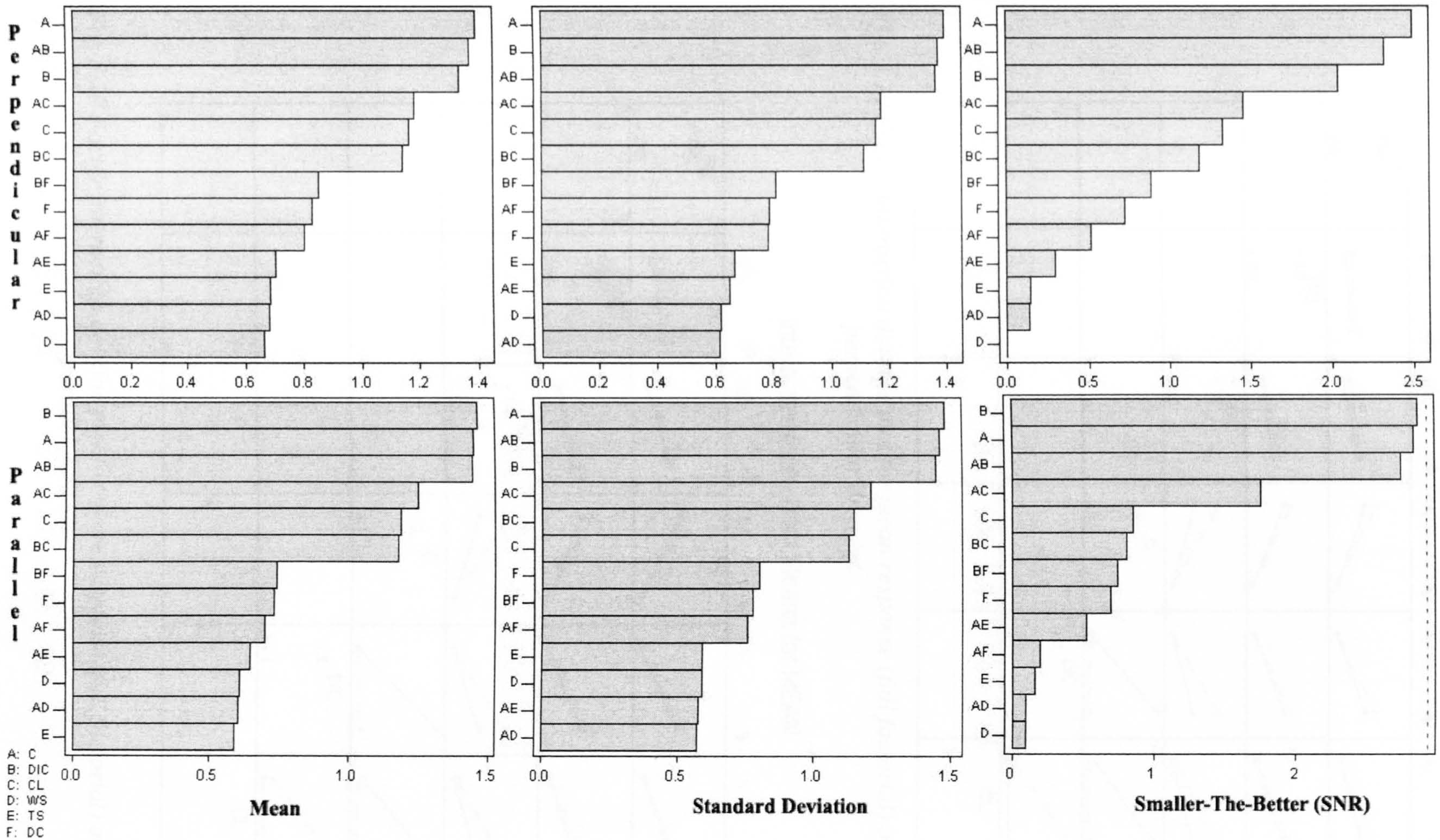


Fig. 3.18 Matrix of Pareto charts of the standardised effects (Taguchi array), Alpha=0.10.

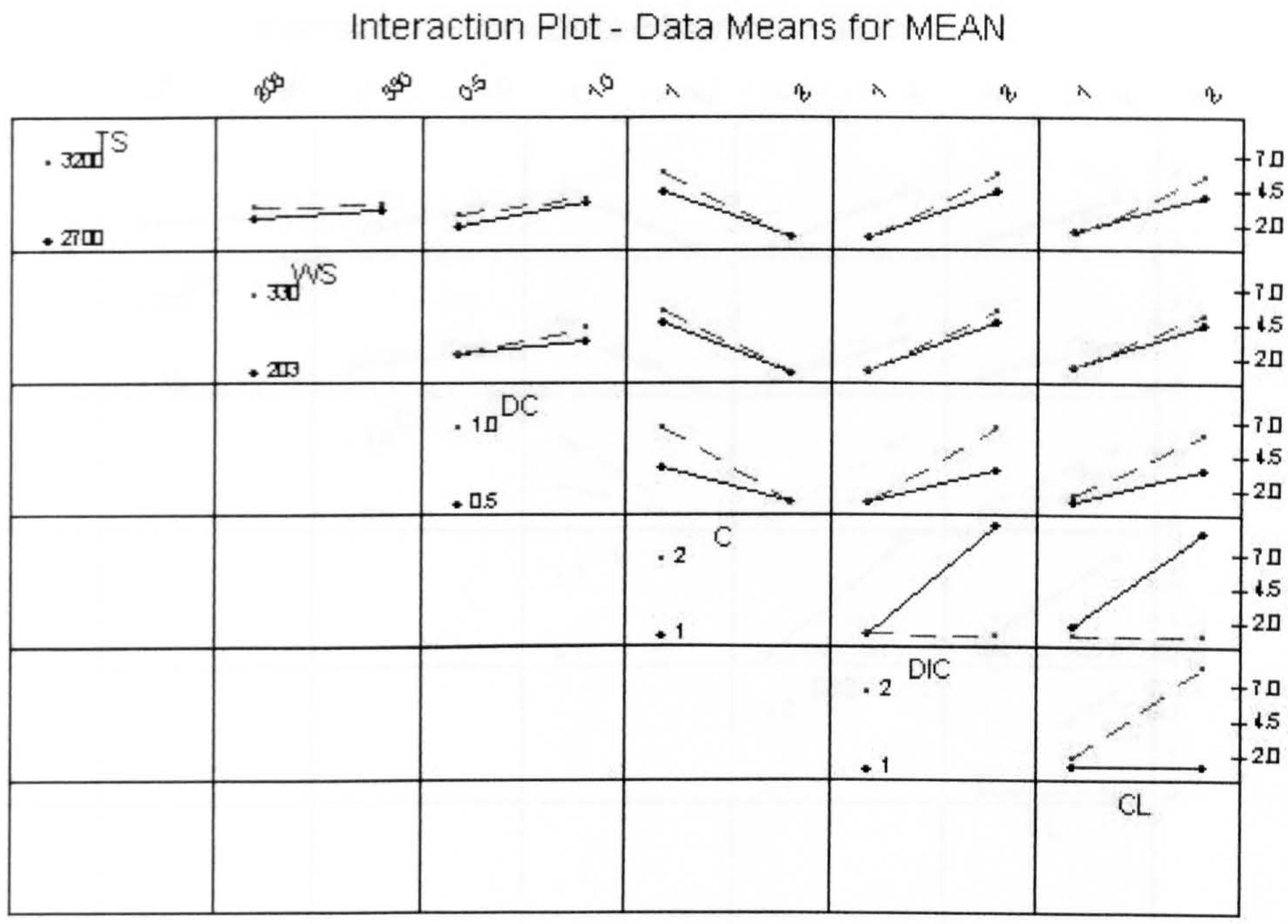


Fig. 3.19 Factor interaction dot-line plot for mean response (full factorial) on the perpendicular data set.

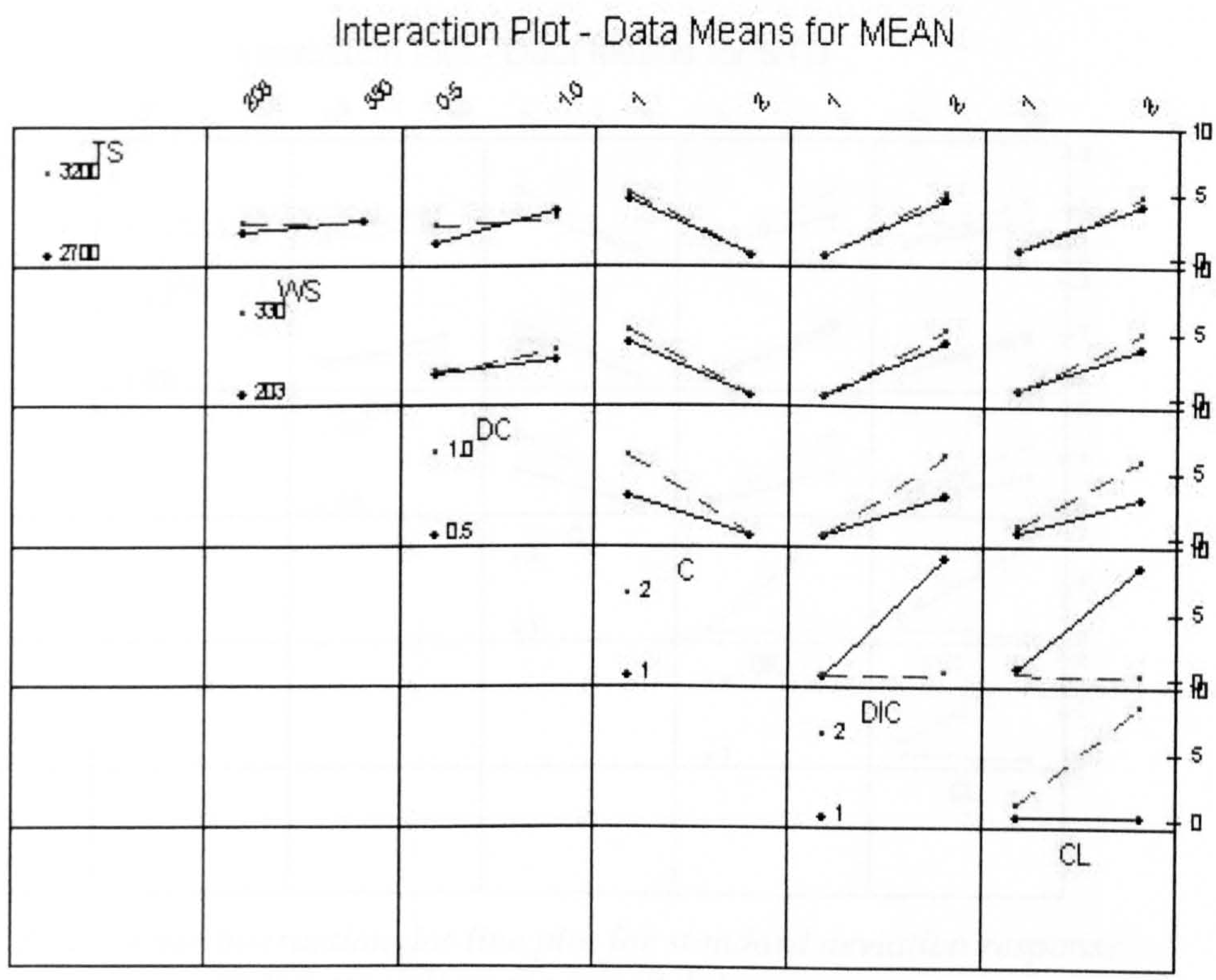


Fig. 3.20 Factor interaction dot-line plot for mean response (full factorial) on the parallel data set.

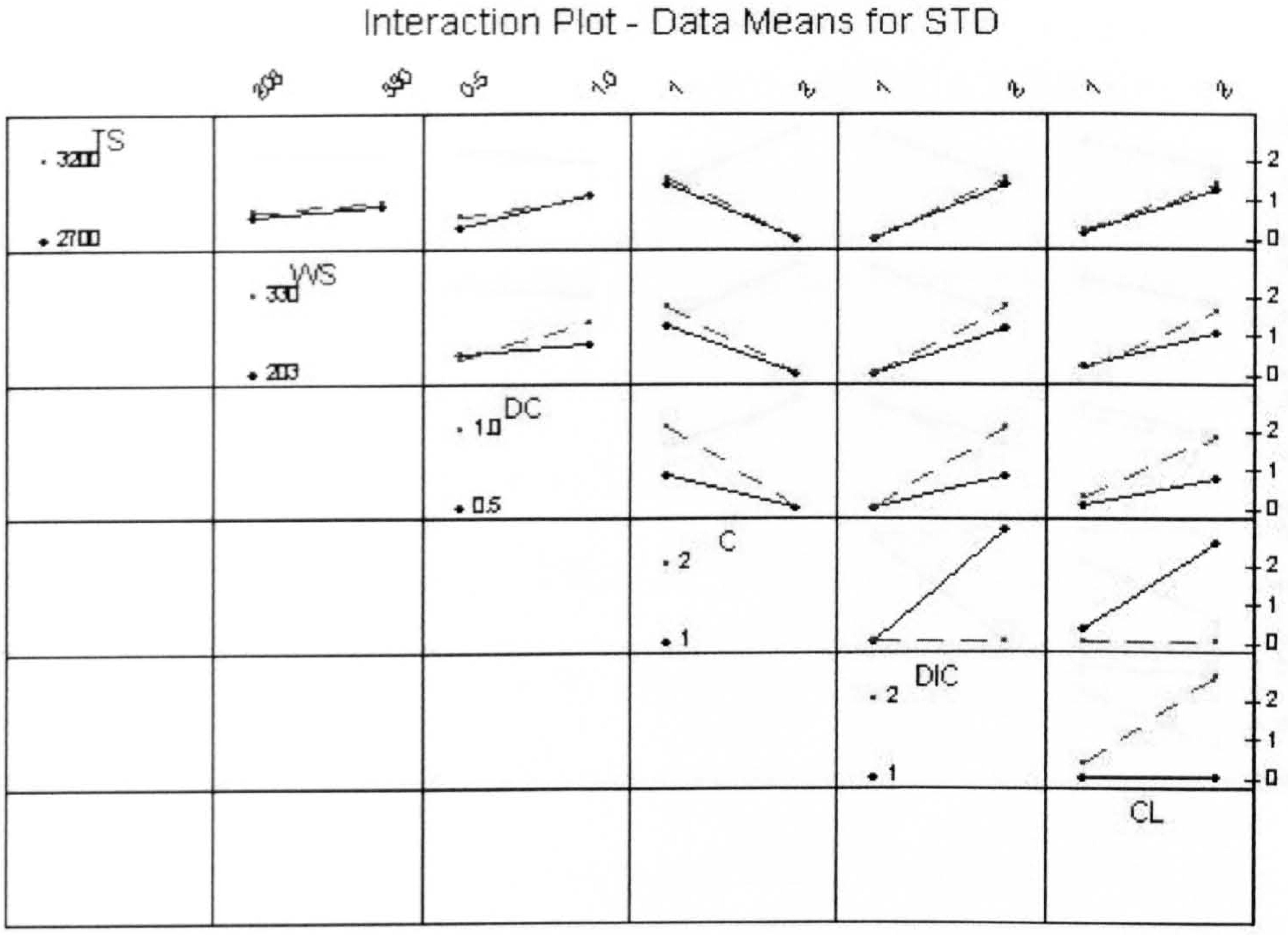


Fig. 3.21 Factor interaction dot-line plot for standard deviation response (full factorial) on the perpendicular data set.

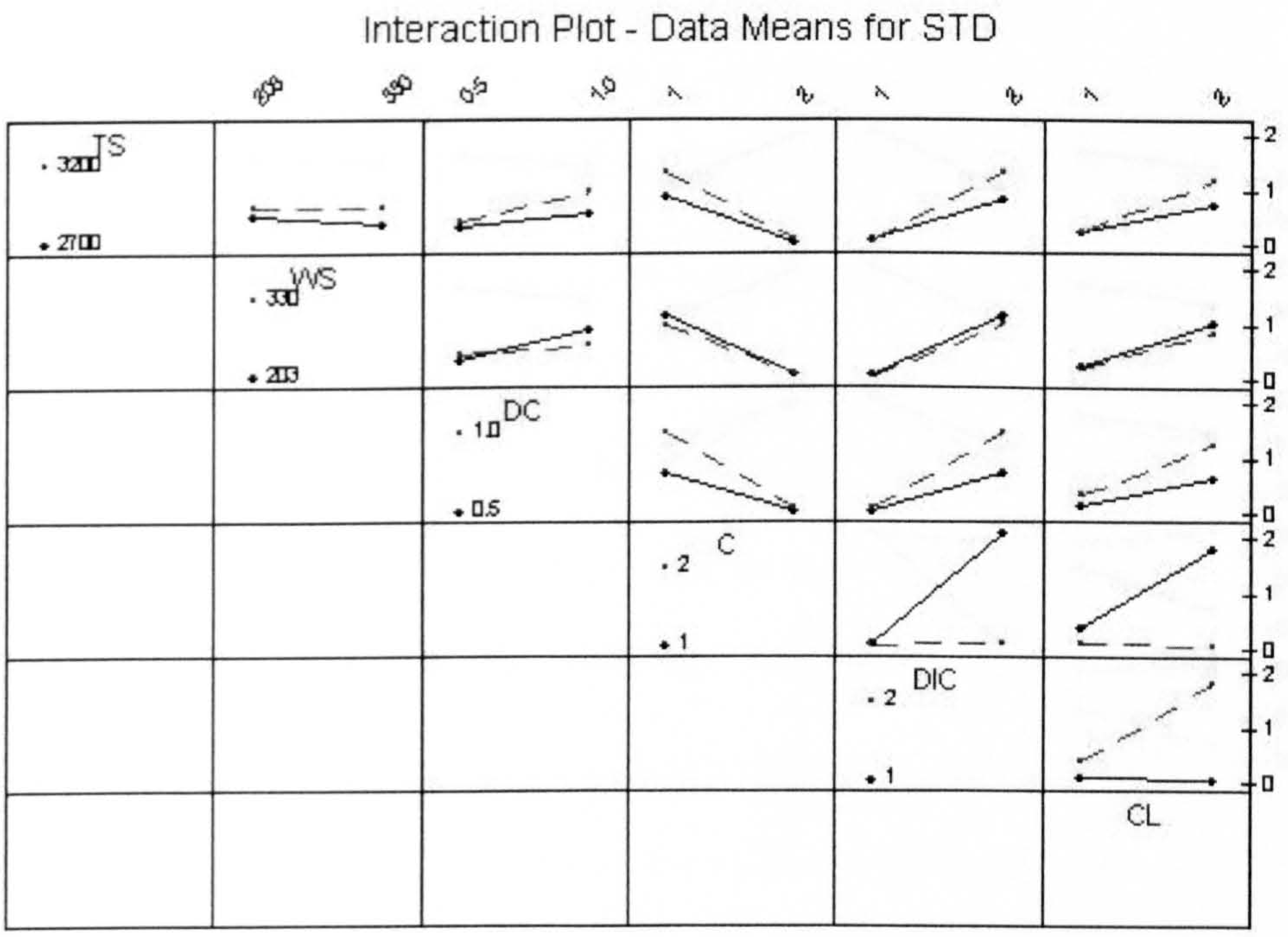


Fig. 3.22 Factor interaction dot-line plot for standard deviation response (full factorial) on the parallel data set.

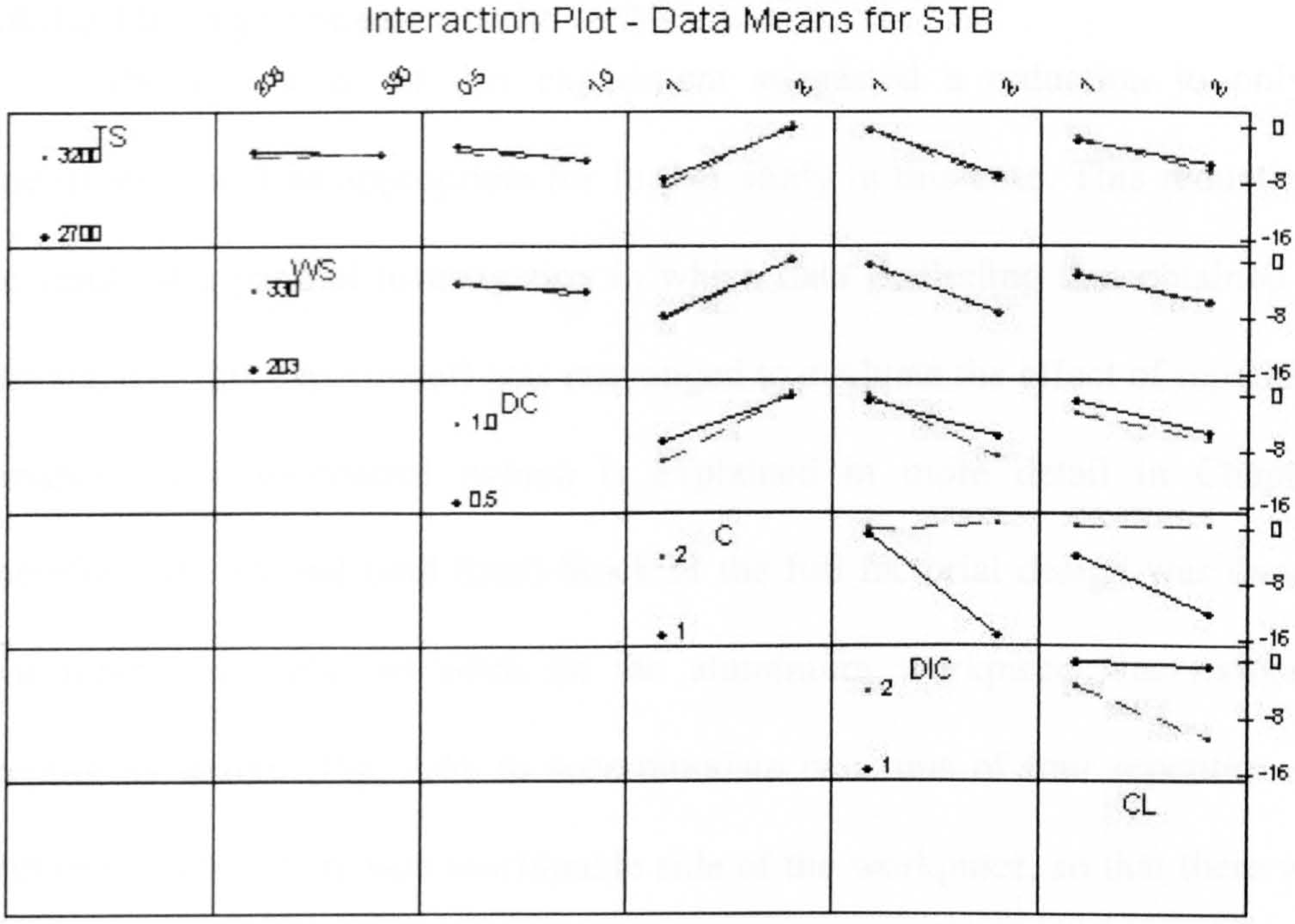


Fig. 3.23 Factor interaction dot-line plot for Signal-to-Noise Ratio (Smaller-The-Better) response (full factorial) on the perpendicular data set.

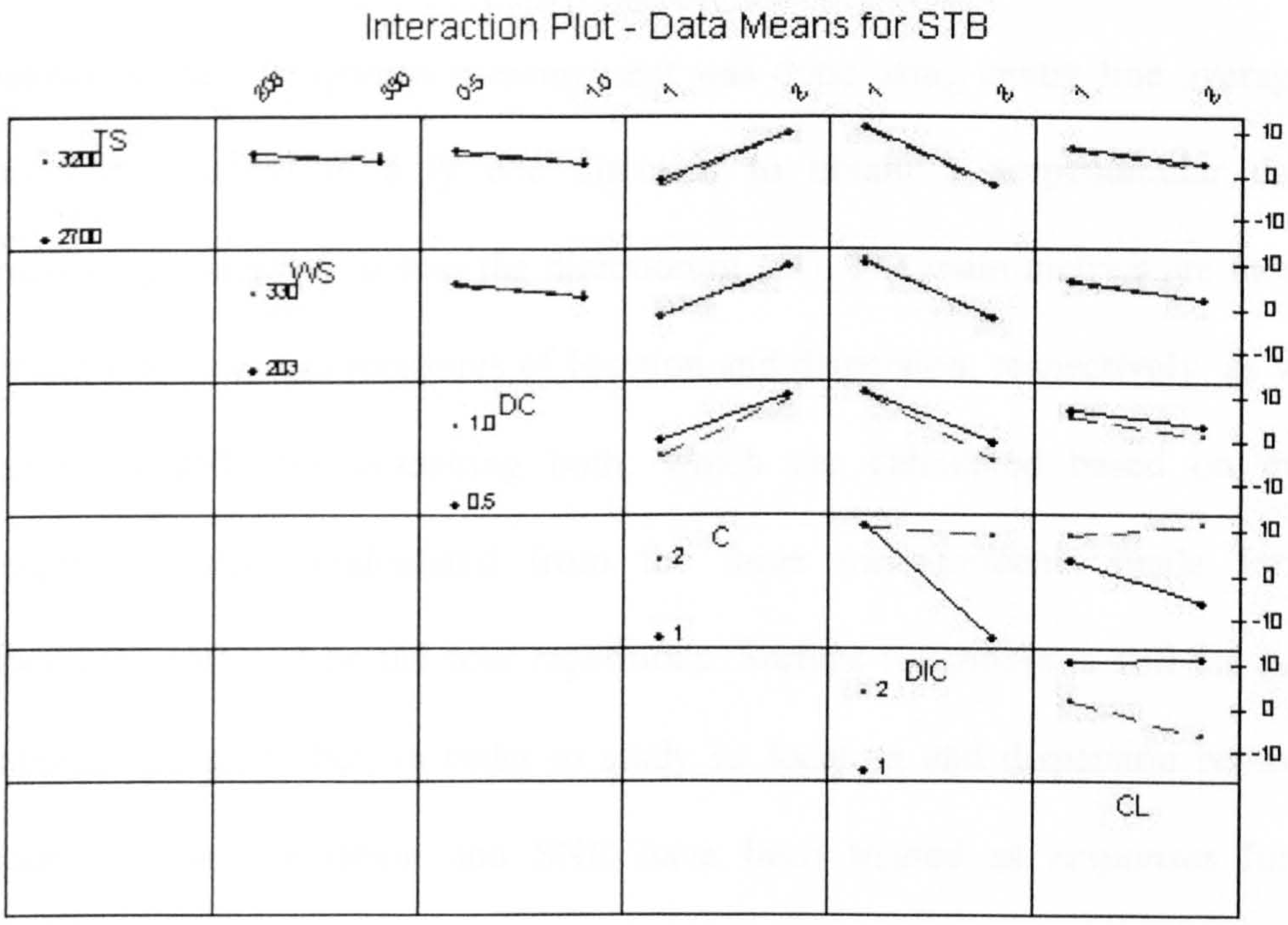


Fig. 3.24 Factor interaction dot-line plot for Signal-to-Noise Ratio (Smaller-The-Better) response (full factorial) on the parallel data set.

3.4.3.2 Milling process study

The first stage of this experiment suggested a reduction to only four repetitions would be appropriate for further study in this case. This reduction was the result of a parallel investigation in which data (including that obtained in the first stage of this experiment) was rearranged to evaluate the effect of repetitions in variance reduction/control (which is explained in more detail in Chapter 6). Therefore, the second (and final) block of the full factorial design was done with four repetitions only, so work on the aluminium workpiece was reorganised, keeping its design (Fig. 3.4), to accommodate two runs of four repetitions each, with one run fitted on each machinable side of the workpiece, so that there was no need to alter the program to handle the CNC operation (Appendix A2). The cutter still used a standard die sinking with square geometry but with only 2-flutes instead. Surface roughness measurement was done using centre line average (R_a) and was assessed in only one direction to obtain a perpendicular data set (measuring roughness across the direction of cut). The main metrics are mean and standard deviation as measures of location and dispersion, respectively, as well as Taguchi's SNR for modelling both, which are calculated based on average roughness values (calculated from the three measurements made for each repetition) obtained on the four repetitions. Surface roughness is still the primary response for study but, in order to study its location and dispersion behaviours, mean, standard deviation and SNR have been treated as *responses* for both experimental arrays (full factorial and Taguchi's L_{16}). Data for Taguchi's L_{16} was extracted from the full factorial data set (as indicated in Section 3.4.2.2). The same linear graphs (Fig. 3.3) utilised for analyses in the first block (Section 3.4.3.1) were applied again for column interactions. Therefore, the last column of the Taguchi array, previously used for errors, was then reserved for the tool type factor. In order to keep a homogeneous design only the first four repetitions from the first block were considered for the full design, so the new full design has four repetitions.

The now complete full factorial array (Appendix B5) was the basis for analysis of significant main factors and up to three-factor interactions. ANOVA analyses of the full factorial with the three responses were done to determine model validity (Table 3.12). It can be seen that model fitting for the three responses was satisfactory for main factors and some two-factor interactions (mean and SNR) but not for the standard deviation response and three-factor interactions. Main factor and interaction significance was studied through ANOVA (using Adjusted SS for tests) and least squares for all responses (Table 3.13). For all responses (Table 3.13), four main factors, six two-factor interactions and four three-factor interactions were found significant. The main factors coolant, direction of cut, number of cuts and tool type were found significant for the three responses (Table 3.13). Two-factor interactions among these four significant main factors were found significant. Additionally, the interactions between depth of cut – coolant and depth of cut – direction of cut, were also found significant for the SNR response only. Regarding the third order interactions, four of them (C-DIC-CL, C-DIC-T, C-CL-T and DIC-CL-T) were found significant for each one of the three responses, together with one interaction (DC-C-DIC) found significant for the SNR response only. There were four unusual observations for three responses (runs 29, 39, 57 and 61) because of their large standardized residual.

Determination of factor significance within the Taguchi array (Appendix B6) was not as successful as with the full factorial. It may be caused by poor model fitting and the possible high amount of confounding underlying the Taguchi design (Table 3.12). Therefore, none of the main factors or interactions were found significant in the ANOVA test (Table 3.14). However, looking at the percentage contribution of the effects chart (Fig. 3.25) it is noticeable that the significant factors ranking for the Taguchi array is very similar to the full factorial, which suggests the presence of underlying effects or confounding preventing ANOVA indicating significance. Despite the results (Fig. 3.25) showing general similarities with both arrays in determining the most significant effects, they failed to be consistent, as some factors not shown important by the full factorial array were so for the Taguchi array. However, the Taguchi array ranks tool speed and workpiece speed among the important factors for all responses, which has been expected since the start of the study. This raises questions about how much/little confounding would be desirable in the design to consider its outcomes reliable. This situation may indicate a need for another type of analysis to provide more evidence, eg determination of significance by Pareto charts. Pareto charts for the three responses (Fig. 3.26) suggest that coolant (C), direction of cut (DIC), workpiece speed (WS) and tool type (T) have the largest effect (in that order) on surface finish. Despite this concurrence in results for these variables, none of the factors was beyond the Pareto reference line, which means that none of these factors were strong enough to be considered potentially important. Notice that again results for the full factorial array show indications that split-plot design characteristics may be present, as has been suggested by preliminary results in the first stage. It is worth mentioning that there was only one unusual observation with a large standardized residual (run 7 for the three responses). It is important to point out the significance of interactions in these Pareto charts (Fig. 3.26) as third-order interactions appear to have an important role for all responses in the full factorial array, above even second-order interactions and main factors.

Main effects and interaction dot-line plots were also evaluated for the three responses (mean, standard deviation and SNR) on both arrays to determine the best design combination. The best possible combination based on full factorial main effect plots for mean response (Fig. 3.27) and SNR (Fig. 3.31) suggested a tool speed of 3200 rev/min, workpiece speed of 203 mm/min, depth of cut of 1.0 mm, coolant on, climbing milling, only one cut per lap and machined with a 4-flute tool type. For standard deviation response (Fig. 3.29) best settings were similar to those for mean response with the exception of workpiece speed and depth of cut, with best settings suggested at 330 mm/min and 0.5 mm, respectively. These best design settings were confirmed with a least-square table for the three responses (Table 3.15).

Two-factor interaction dot-line plots were also evaluated (Fig. 3.33 to 3.35) paying special attention to significant interactions not reflected in the ANOVA test. For instance, interactions involving depth of cut (with tool speed, coolant and direction of cut) were found significant for the mean and SNR responses. For the standard deviation response extra significance was noticed around depth of cut, which showed strong interactions with number of cuts and tool type.

Before proceeding with the confirmation runs suggested by Taguchi (1987), several similarities among the response patterns (firstly with the measurement method comparison study and then with this process study) pointed to possible correlations amongst them. Therefore, correlation studies were carried out on both experimental arrays (full factorial and Taguchi) (Table 3.16). Strong correlation between mean and SNR was found in data from both arrays. Notice that correlation is stronger in the Taguchi array even though it may be influenced by the correlation between mean and standard deviation in that array. Also, it is worthwile to point out the similarity in sign and value of the correlation mean-SNR as both arrays correlated in a similar way. This correlation between mean and SNR proves once more what Taher and Anderson (1993a, 1993b) found out in another metal cutting process. High levels of correlation present in the Taguchi array, particularly between mean and standard deviation, may indicate either the presence of some noise within the design or proof of the criticisms of Taguchi designs already suggested by statisticians (Section 2.4).

Based on the best design settings suggested by results obtained from Taguchi arrays, confirmation runs were carried out considering both linear graphs studied (Table 3.17). Settings utilised for the confirmation experiments of both linear graphs are equivalent to runs 46 and 76 from the full factorial array respectively. Unfortunately, both confirmation runs failed to suggest improved settings when comparing both results. This is not unusual and is often presented as a criticism of this aspect of the Taguchi approach by statisticians.

		Source	DF	Seq SS	Adj SS	Adj MS	F	p>F
Mean	Full Factorial	Main Effects	7	604.4	604.4	86.343	13.2	0
		2-Way Interactions	21	934.3	934.3	44.491	6.8	0
		3-Way Interactions	35	737.9	737.9	21.082	3.22	0
		Residual Error	64	418.7	418.7	6.542		
		Total	127	2695.3				
	Taguchi (LGII)	Main Effects	7	69.045	69.045	9.864	2.45	0.32
		2-Way Interactions	6	54.828	54.828	9.138	2.27	0.337
		Residual Error	2	8.043	8.043	4.022		
		Total	15	131.92				
	Taguchi (LGIV)	Main Effects	7	69.05	69.05	9.86	2.45	0.32
		2-Way Interactions	6	54.83	54.83	9.14	2.27	0.34
		Residual Error	2	8.04	8.04	4.02		
		Total	15	131.92				
Standard Deviation	Full Factorial	Main Effects	7	16.2	16.2	2.3137	14.46	0
		2-Way Interactions	21	21.4	21.4	1.0193	6.37	0
		3-Way Interactions	35	15.81	15.81	0.4518	2.82	0
		Residual Error	64	10.24	10.24	0.16		
		Total	127	63.65				
	Taguchi (LGII)	Main Effects	7	6.186	6.186	0.8837	1.64	0.43
		2-Way Interactions	6	4.78	4.78	0.7967	1.48	0.456
		Residual Error	2	1.077	1.077	0.5386		
		Total	15	12.043				
	Taguchi (LGIV)	Main Effects	7	6.19	6.19	0.88	1.64	0.43
		2-Way Interactions	6	4.78	4.78	0.80	1.48	0.46
		Residual Error	2	1.08	1.08	0.54		
		Total	15	12.04				

Table 3.12 ANOVA model fitting test for the full factorial (original data in appendix B5) and Taguchi (original data in appendix B6) arrays (milling case study).....continued

		Source	DF	Seq SS	Adj SS	Adj MS	F	p>F
Smaller-the-Better	Full Factorial	Main Effects	7	1567.1	1567.1	223.869	60.24	0
		2-Way Interactions	21	1713.3	1713.3	81.588	21.95	0
		3-Way Interactions	35	904.7	904.7	25.85	6.96	0
		Residual Error	64	237.8	237.8	3.716		
		Total	127	4423				
	Taguchi (LGII)	Main Effects	7	302.798	302.798	43.257	39.87	0.025
		2-Way Interactions	6	225.4	225.4	37.567	34.63	0.028
		Residual Error	2	2.17	2.17	1.085		
		Total	15	530.368				
	Taguchi (LGIV)	Main Effects	7	302.80	302.80	43.26	39.87	0.03
		2-Way Interactions	6	225.40	225.40	37.57	34.63	0.03
		Residual Error	2	2.17	2.17	1.09		
		Total	15	530.37				

Table 3.12 continuation…ANOVA model fitting test for the full factorial (original data in appendix B5) and Taguchi (original data in appendix B6) arrays (milling case study).

		Mean		Std. Dev.		STB	
Source	DF	F	p>f	F	p>F	F	p>F
TS	1	0.67	0.417	3.38	0.071	0.06	0.814
WS	1	0.85	0.361	2.08	0.154	0	0.999
DC	1	4.21	0.044	0.51	0.479	4.03	0.049
C	1	25.56	0	32.09	0	178.6	0
DIC	1	24.67	0	31.12	0	151.66	0
CL	1	18.29	0	13.46	0	51.38	0
TOOL	1	18.14	0	18.58	0	35.95	0
TS*WS	1	0.36	0.553	0.68	0.412	1.36	0.248
TS*DC	1	0.21	0.65	0.75	0.39	2.92	0.093
TS*C	1	0.85	0.36	2.97	0.09	1.97	0.166
TS*DIC	1	0.68	0.412	2.84	0.097	0.15	0.701
TS*CL	1	1.09	0.301	4.43	0.039	2.91	0.093
TS*TOOL	1	0.74	0.392	2.83	0.098	0.48	0.493
WS*DC	1	1.72	0.194	1.09	0.301	0.23	0.631
WS*C	1	0.88	0.351	2.31	0.133	0.04	0.849
WS*DIC	1	0.8	0.373	2.37	0.129	0.04	0.843

Table 3.13 ANOVA using Adjusted SS for Tests for the full factorial array (original data in appendix B5) (milling case study)….continued

Source	DF	Mean F	Mean p>f	Std. Dev. F	Std. Dev. p>F	STB F	STB p>F
WS*CL	1	0.85	0.36	0.49	0.488	0.07	0.79
WS*TOOL	1	1.13	0.291	1.22	0.273	1.26	0.266
DC*C	1	4.65	0.035	0.23	0.634	10.3	0.002
DC*DIC	1	4.93	0.03	0.25	0.619	14.68	0
DC*CL	1	2.68	0.106	2.86	0.096	0.17	0.683
DC*TOOL	1	4.02	0.049	0.74	0.393	3.79	0.056
C*DIC	1	24.51	0	31.44	0	150.14	0
C*CL	1	18.1	0	13.05	0.001	48.37	0
C*TOOL	1	21.03	0	19.44	0	92.12	0
DIC*CL	1	17.83	0	12.82	0.001	43.37	0
DIC*TOOL	1	18.85	0	19.39	0	47.47	0
CL*TOOL	1	16.88	0	11.61	0.001	39.2	0
TS*WS*DC	1	0.17	0.682	0.14	0.714	1.07	0.305
TS*WS*C	1	0.31	0.578	0.62	0.435	0.66	0.419
TS*WS*DIC	1	0.34	0.56	0.41	0.524	1.01	0.319
TS*WS*CL	1	0.21	0.651	0.63	0.43	0.27	0.603
TS*WS*TOOL	1	0.23	0.633	0.09	0.759	0.15	0.7
TS*DC*C	1	0.19	0.665	0.59	0.443	2.11	0.151
TS*DC*DIC	1	0.18	0.675	0.58	0.449	1.97	0.165
TS*DC*CL	1	0.07	0.791	0.33	0.567	0.49	0.485
TS*DC*TOOL	1	0.02	0.892	0.19	0.668	0.61	0.439
TS*C*DIC	1	0.64	0.425	2.42	0.125	0.03	0.866
TS*C*CL	1	1.11	0.295	4.58	0.036	3.62	0.062
TS*C*TOOL	1	0.68	0.412	3.07	0.085	0.12	0.728
TS*DIC*CL	1	0.97	0.33	4.35	0.041	1.19	0.279
TS*DIC*TOOL	1	0.7	0.407	2.89	0.094	0.13	0.724
TS*CL*TOOL	1	1.01	0.32	3.5	0.066	1.68	0.2
WS*DC*C	1	1.97	0.165	0.85	0.361	2.46	0.122
WS*DC*DIC	1	1.69	0.199	0.86	0.357	0.16	0.693
WS*DC*CL	1	1.72	0.194	0.17	0.677	0.65	0.424
WS*DC*TOOL	1	1.62	0.208	1.08	0.303	0.09	0.76
WS*C*DIC	1	0.77	0.382	2.2	0.143	0.25	0.621
WS*C*CL	1	0.79	0.377	0.56	0.458	0.02	0.892
WS*C*TOOL	1	1.02	0.317	1.07	0.304	0.23	0.63
WS*DIC*CL	1	0.95	0.334	0.55	0.461	0.54	0.465
WS*DIC*TOOL	1	1.11	0.296	0.58	0.448	0.89	0.348
WS*CL*TOOL	1	1.11	0.295	0.39	0.533	1.46	0.231
DC*C*DIC	1	4.56	0.037	0.17	0.684	8.29	0.005
DC*C*CL	1	2.98	0.089	2.67	0.107	0.27	0.603
DC*C*TOOL	1	3.99	0.05	0.94	0.336	3.39	0.07
DC*DIC*CL	1	3.15	0.081	2.31	0.134	1.01	0.32
DC*DIC*TOOL	1	3.86	0.054	0.85	0.36	2.23	0.14

Table 3.13 ANOVA using Adjusted SS for Tests for the full factorial array (original data in appendix B5) (milling case study)....continued

Source	DF	Mean F	Mean p>f	Std. Dev. F	Std. Dev. p>F	STB F	STB p>F
DC*CL*TOOL	1	2.68	0.106	2.8	0.099	0.05	0.824
C*DIC*CL	1	18.42	0	12.84	0.001	54.24	0
C*DIC*TOOL	1	20.78	0	19.02	0	86.81	0
C*CL*TOOL	1	16.85	0	13.06	0.001	39.29	0
DIC*CL*TOOL	1	15.95	0	11.46	0.001	26.01	0
Error	64	418.712		10.2394		237.843	
Total	127	2695.285		63.653		4423.018	

Table 3.13 Continuation.......ANOVA using Adjusted SS for Tests for the full factorial array (original data in appendix B5) (milling case study).

	Source	DF	Mean F	Mean p>f	Std. Dev. F	Std. Dev. p>F	STB F	STB p>F
Linear Graph II	C	1	3.79	0.191	2.67	0.244	93.49	0.011
	TS	1	1.58	0.336	1.34	0.367	16.51	0.056
	WS	1	2.8	0.236	1.52	0.343	36.48	0.026
	DC	1	1.31	0.371	1.01	0.421	9.08	0.095
	DIC	1	3.63	0.197	2.35	0.265	83.56	0.012
	CL	1	1.46	0.351	1.2	0.388	12.04	0.074
	T	1	2.6	0.248	1.41	0.357	27.94	0.034
	C*TS	1	1.58	0.336	1.25	0.38	16.05	0.057
	C*WS	1	3.24	0.214	1.49	0.347	64.57	0.015
	C*DC	1	1.18	0.39	1.01	0.42	4.52	0.167
	C*DIC	1	3.58	0.199	2.62	0.247	80.82	0.012
	C*CL	1	1.29	0.373	1.06	0.412	5.41	0.145
	C*T	1	2.76	0.239	1.45	0.352	36.39	0.026
	Error	2	8.043		1.0772		2.17	
	Total	15	131.917		12.0432		530.368	
Linear Graph IV	C	1	3.79	0.191	2.67	0.244	93.49	0.011
	TS	1	1.58	0.336	1.34	0.367	16.51	0.056
	WS	1	2.80	0.236	1.52	0.343	36.48	0.026
	DC	1	1.31	0.371	1.01	0.421	9.08	0.095
	DIC	1	3.63	0.197	2.35	0.265	83.56	0.012
	CL	1	1.46	0.351	1.20	0.388	12.04	0.074
	T	1	2.60	0.248	1.41	0.357	27.94	0.034
	C*TS	1	1.58	0.336	1.25	0.380	16.05	0.057
	C*WS	1	3.24	0.214	1.49	0.347	64.57	0.015
	C*DC	1	1.18	0.390	1.01	0.420	4.52	0.167
	C*DIC	1	3.58	0.199	2.62	0.247	80.82	0.012
	C*CL	1	1.29	0.373	1.06	0.412	5.41	0.145
	C*T	1	2.76	0.239	1.45	0.352	36.39	0.026
	Error	2	8.043		1.077		2.170	
	Total	15	131.917		12.043		530.368	

Table 3.14 ANOVA using Adjusted SS for Tests for the Taguchi array LGII and LGIV (original data in appendix B6) (milling case study).

Factor	Level	Full factorial array Mean	Full factorial array Std. Dev.	Full factorial array SNR (STB)	Taguchi array Mean	Taguchi array Std. Dev.	Taguchi array SNR (STB)
Tool speed (rev/min) (TS)	3200	2.38	0.31	-2.72	1.087	0.076	-0.648
	2700	2.01	0.18	-2.64	1.837	0.229	-2.952
Workpiece speed (mm/min) (WS)	203	1.99	0.3	-2.68	1.804	0.224	-2.664
	330	2.41	0.2	-2.68	1.120	0.081	-0.935
Depth of cut (mm) (DC)	1	2.66	0.22	-3.02	1.116	0.088	-0.815
	0.5	1.73	0.27	-2.34	1.808	0.218	-2.785
Coolant (C)	Off	3.34	0.45	-4.96	1.902	0.241	-3.425
	On	1.05	0.05	-0.4	1.022	0.064	-0.175
Direction of cut (DIC)	Climb	1.07	0.05	-0.58	1.014	0.050	-0.119
	Conventional	3.32	0.44	-4.78	1.910	0.255	-3.481
Number of cuts (CL)	1	1.23	0.12	-1.46	1.128	0.109	-0.952
	2	3.16	0.38	-3.9	1.796	0.197	-2.648
Tool type (T)	4-flute	3.16	0.4	-3.7	1.758	0.211	-2.365
	2-flute	1.23	0.1	-1.66	1.166	0.095	-1.235

Table 3.15 Summary table for the main-overall location and dispersion effects for the full factorial (original data in appendix B5) and Taguchi (original data in appendix B6) array

	Full factorial design Mean	Full factorial design Standard Deviation	Taguchi array Mean	Taguchi array Standard Deviation
Standard Deviation	0.606		0.994	
Smaller-The-Better	-0.906	-0.785	-0.955	-0.933

Table 3.16 Response correlations (Pearson) for the milling process study for the full factorial (original data in appendix B5) and Taguchi (original data in appendix B6) array

	Factors							Roughness		
Test	TS	WS	DC	C	DIC	CL	T	AVG	STD	STB
LG II	3200	330	1	On	Climb	1	2-flute	1.91	0.0354	-5.6610
LG IV	3200	330	1	On	Climb	1	4-flute	1.1175	0.0106	-0.907

Table 3.17 Confirmation runs (Taguchi array – Milling process study)

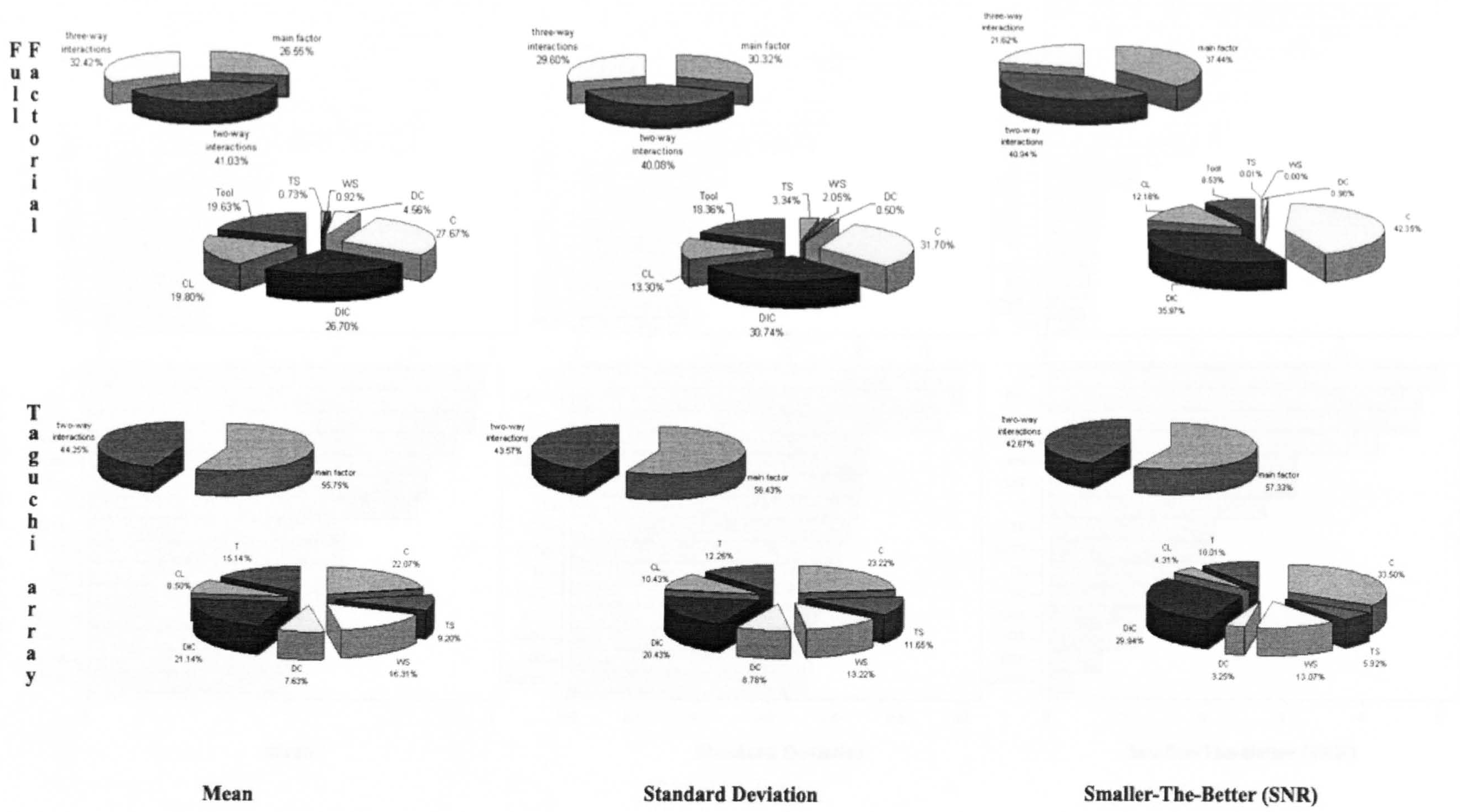


Fig. 3.25 Surface finish percentage contribution of the effects (full factorial and Taguchi arrays).

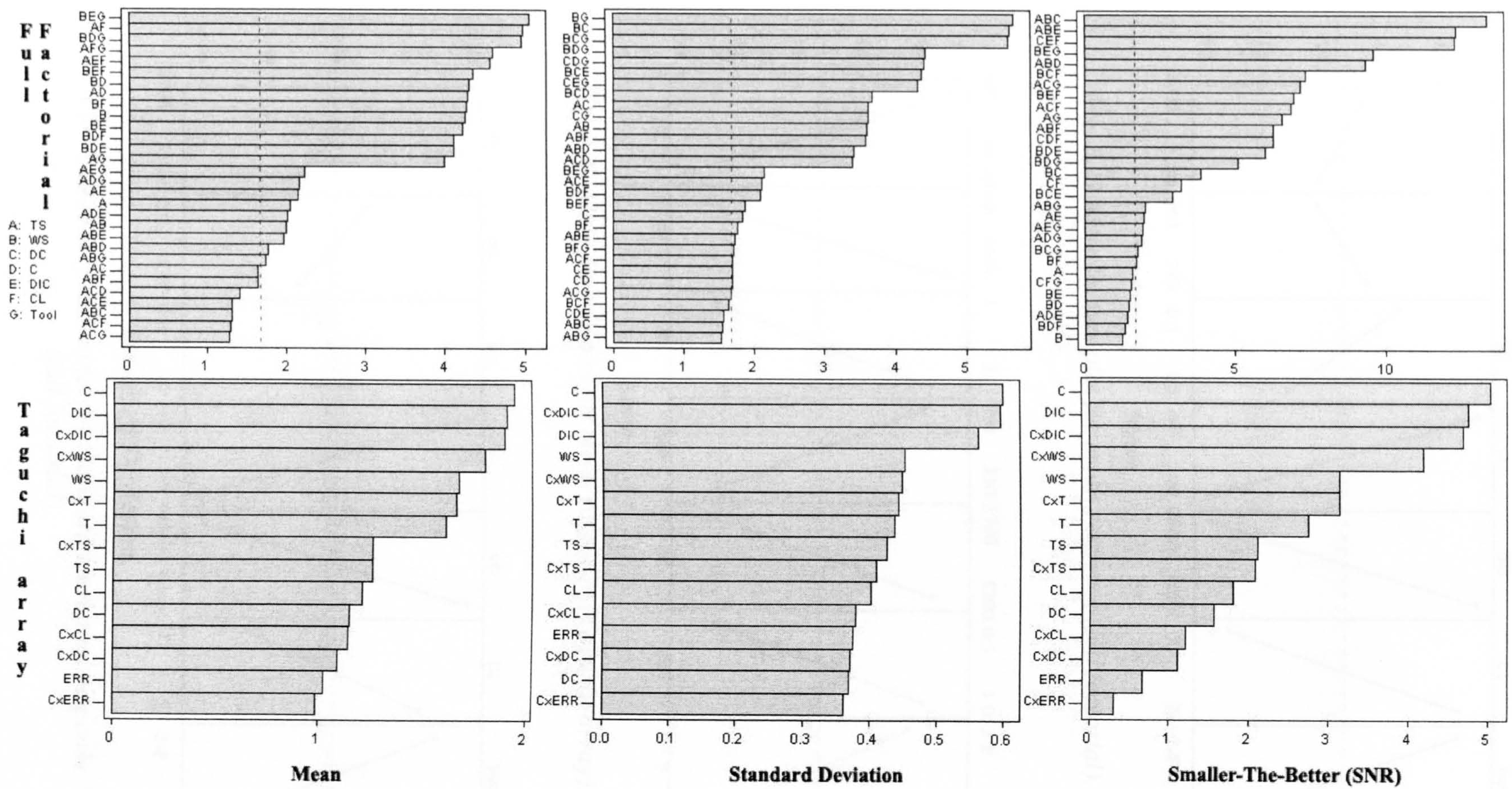


Fig. 3.26 Matrix of Pareto charts of the standardised effects (Taguchi array), Alpha=0.10.

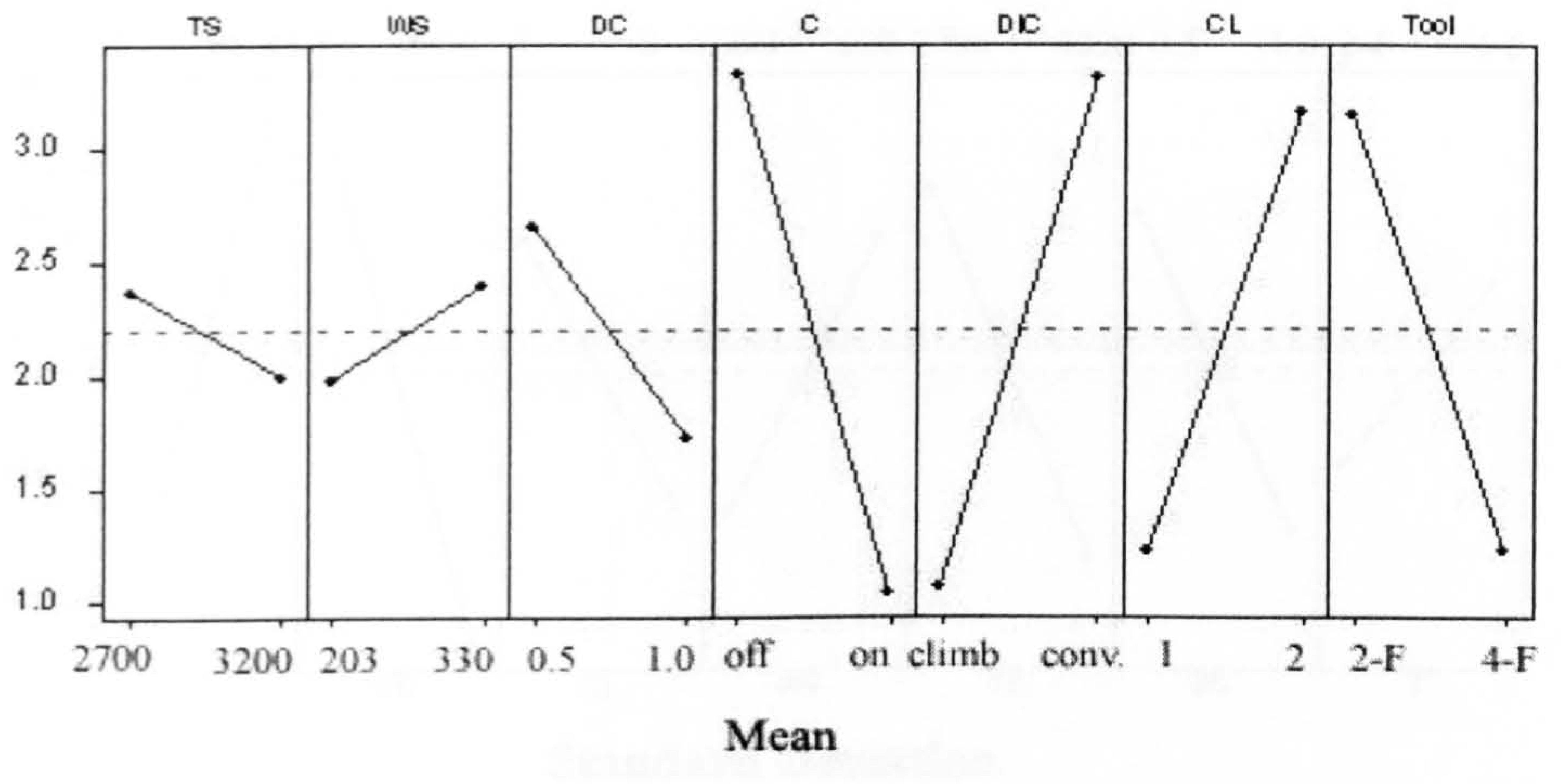


Fig. 3.27 Main factors plot for mean response (full factorial).

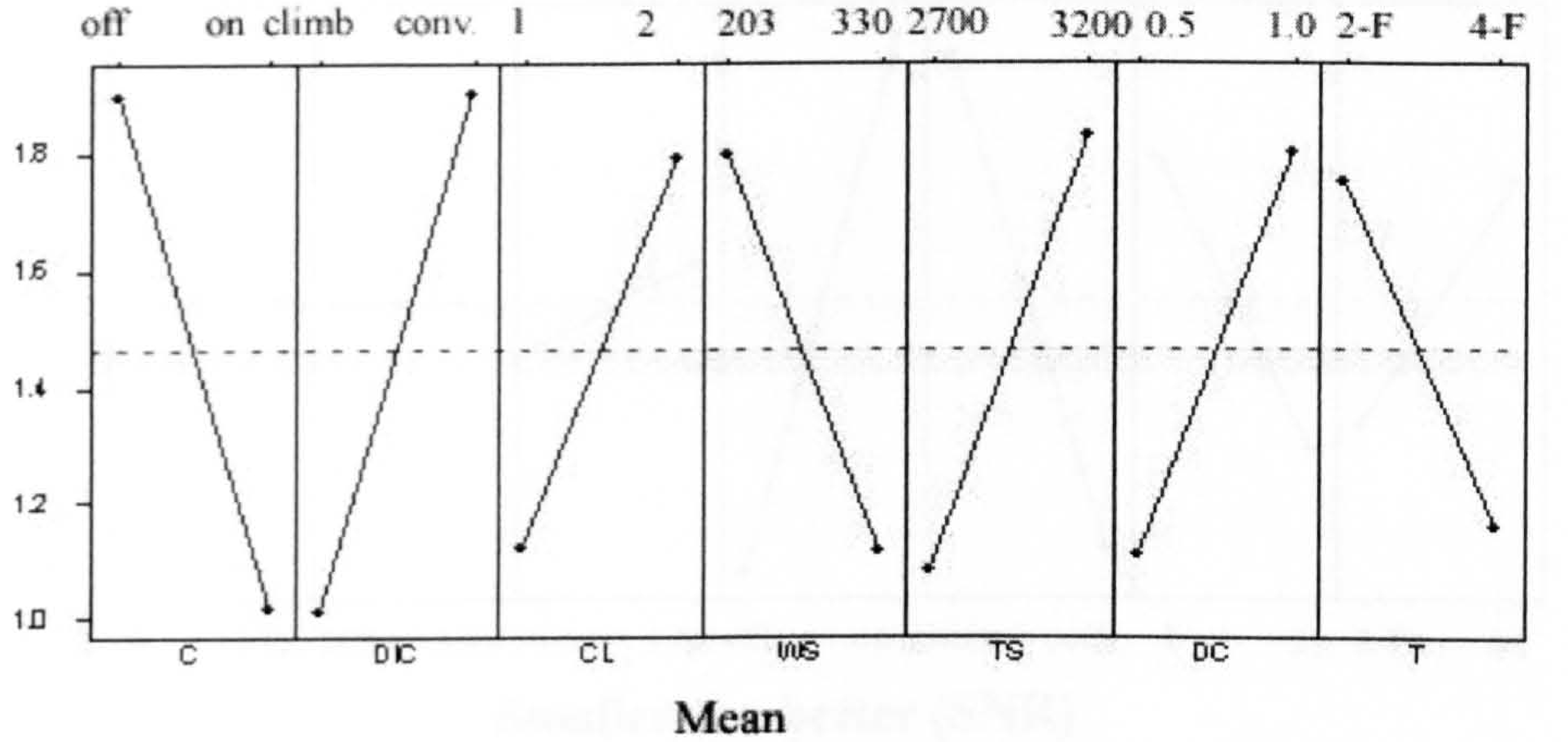


Fig. 3.28 Main factors plot for mean response (Taguchi array).

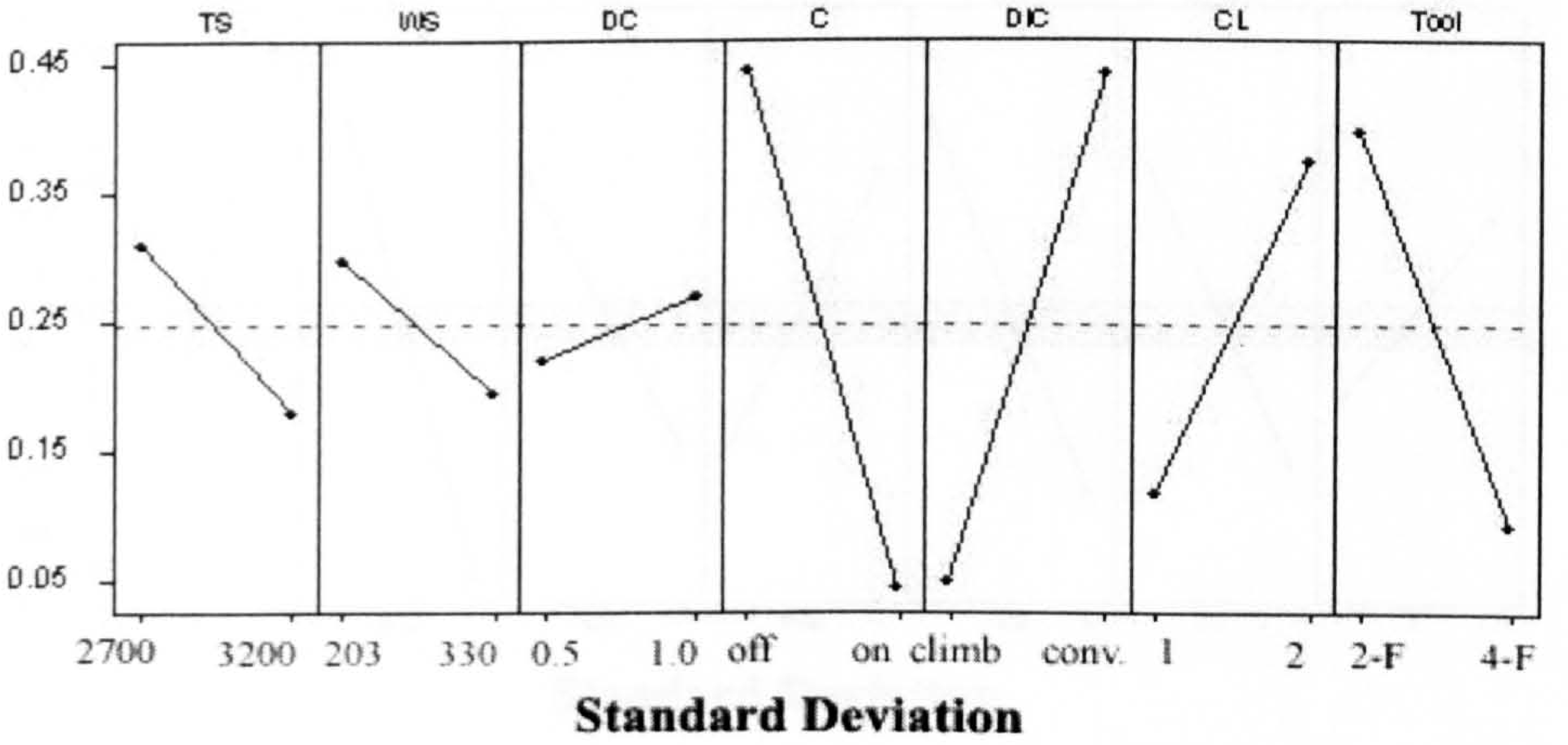


Fig. 3.29 Main factors plot for Standard Deviation response (full factorial).

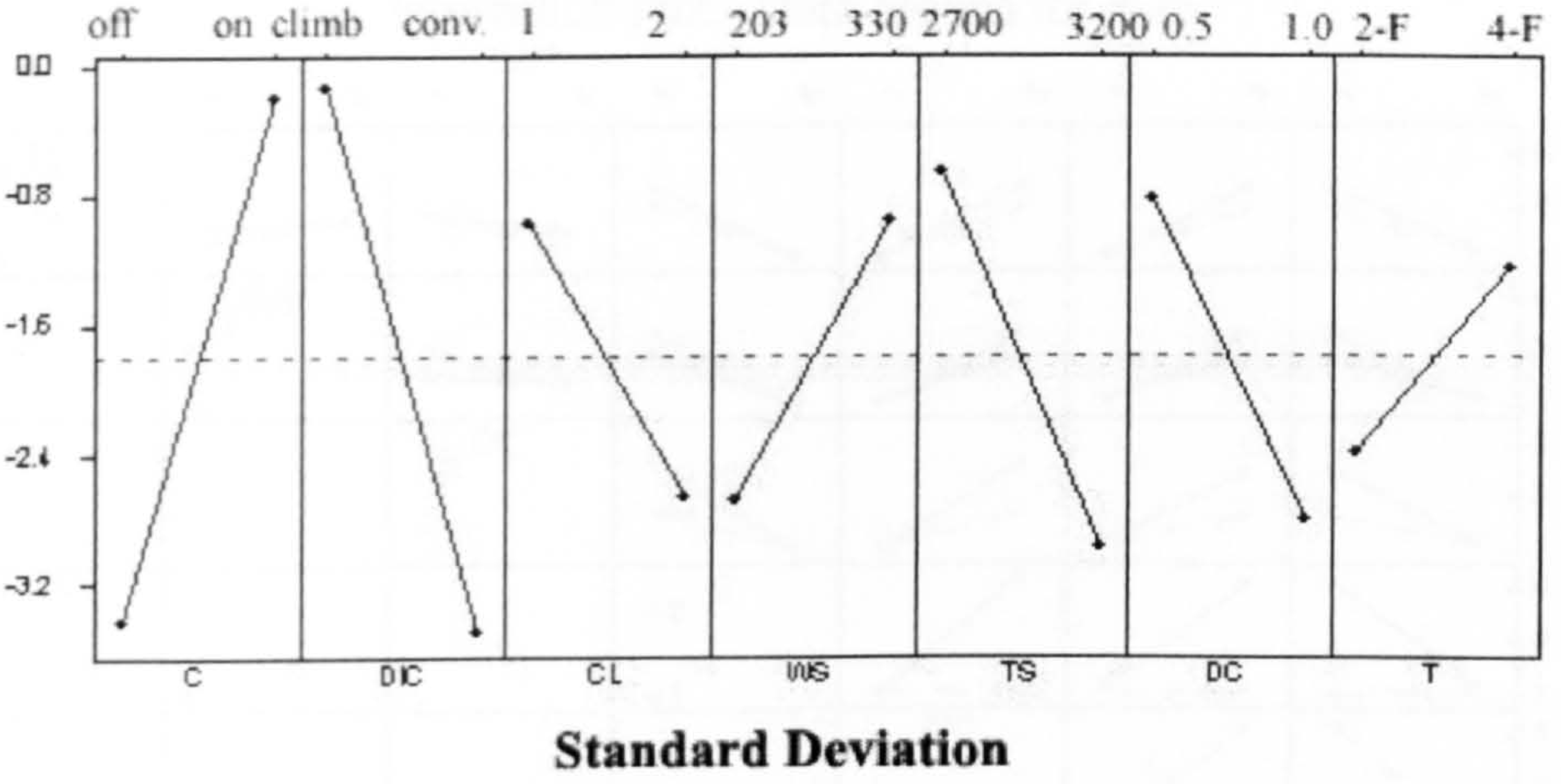


Fig. 3.30 Main factors plot for Standard Deviation response (Taguchi array).

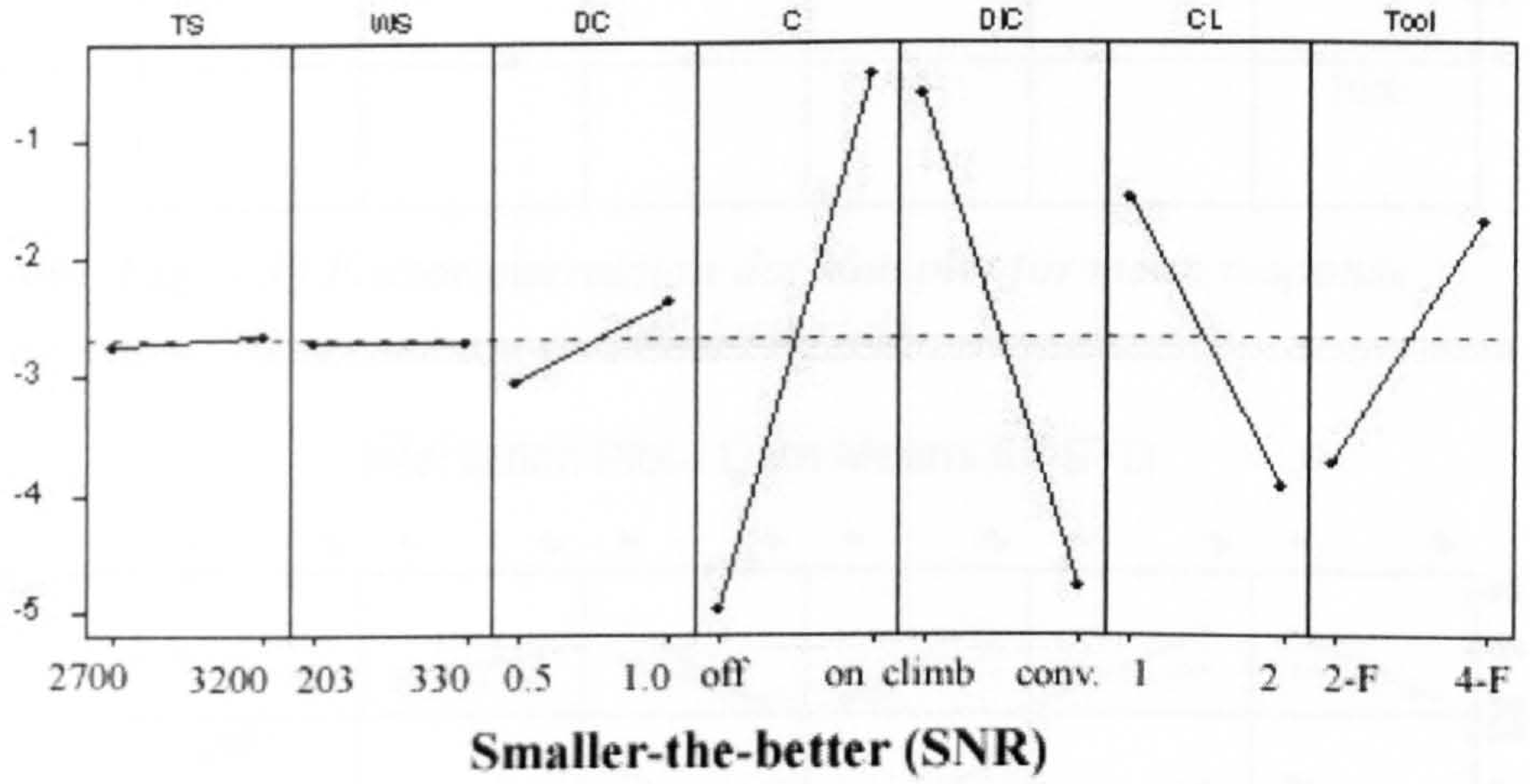


Fig. 3.31 Main factors plot for Smaller-The-Better (SNR) response (full factorial).

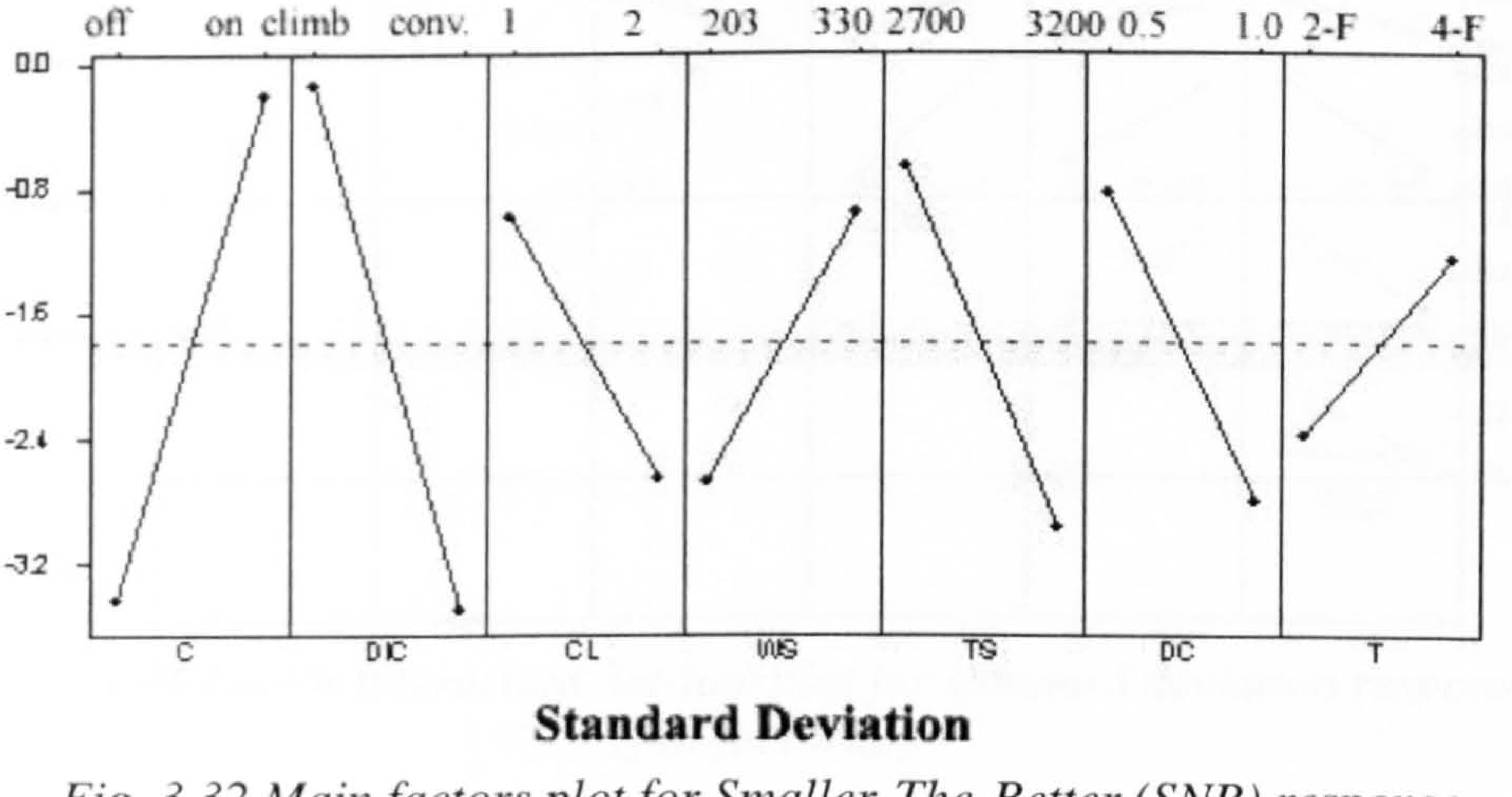


Fig. 3.32 Main factors plot for Smaller-The-Better (SNR) response (Taguchi array).

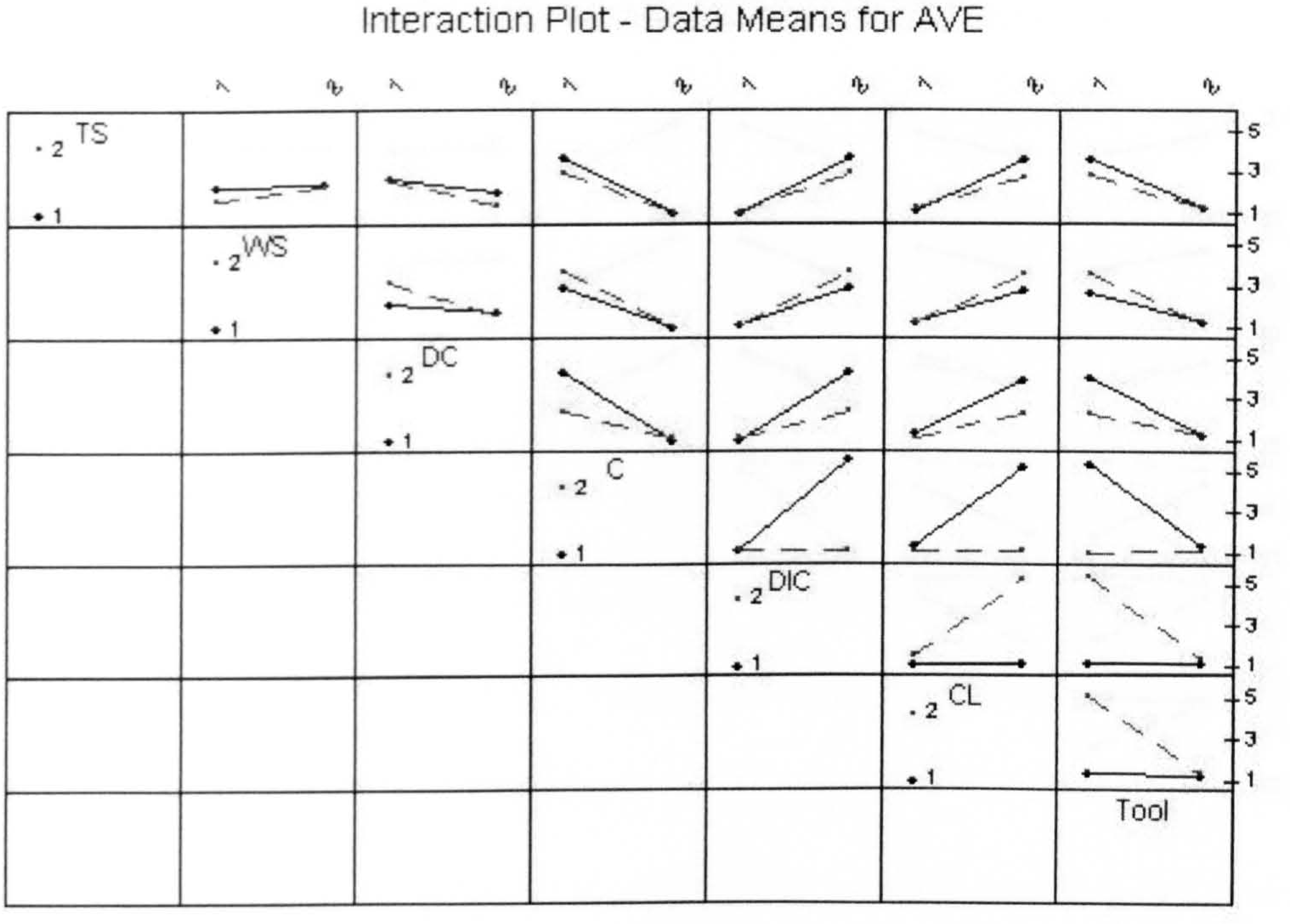


Fig. 3.33 Factor interaction dot-line plot for mean response (full factorial).

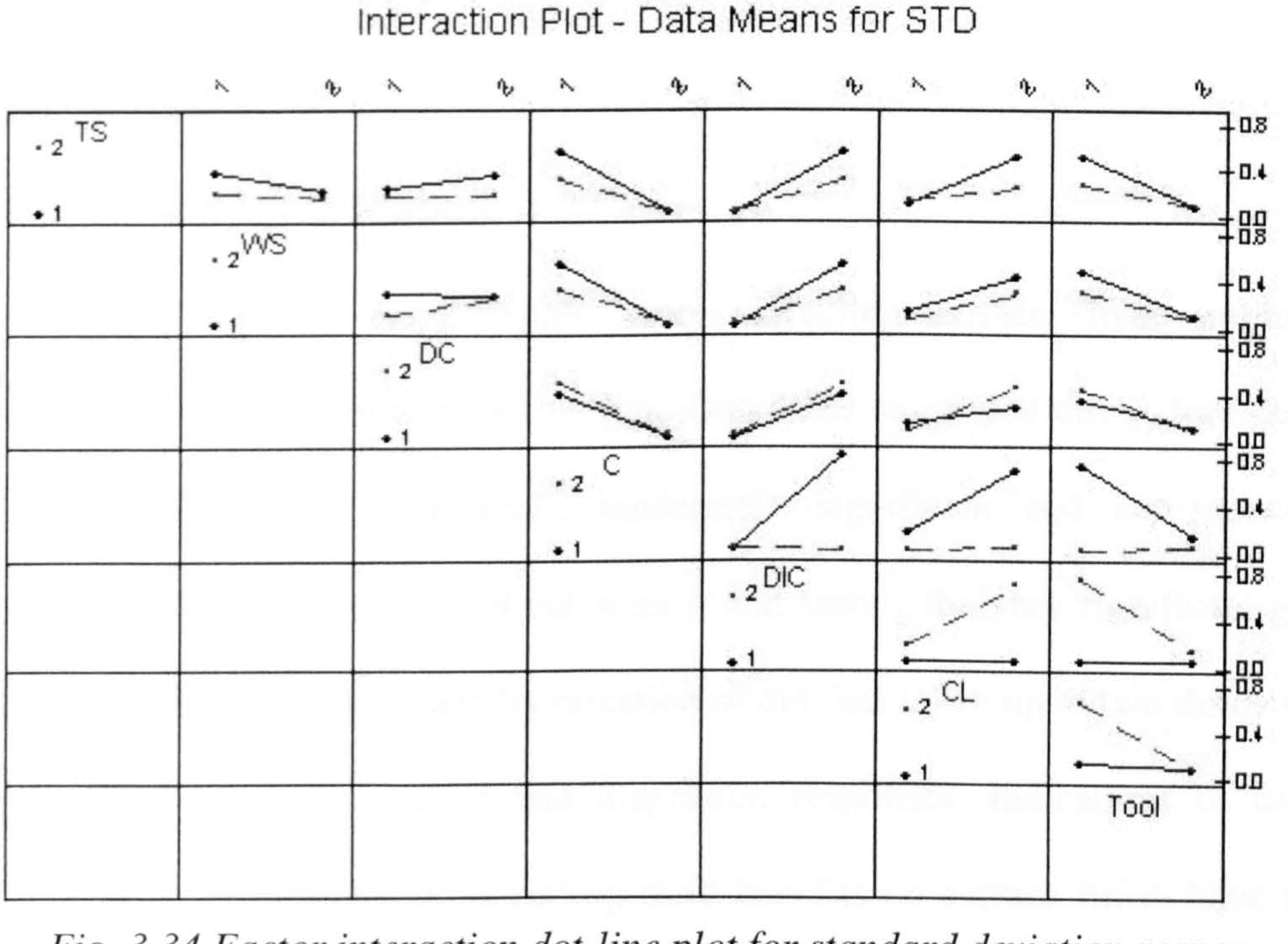


Fig. 3.34 Factor interaction dot-line plot for standard deviation response (full factorial)

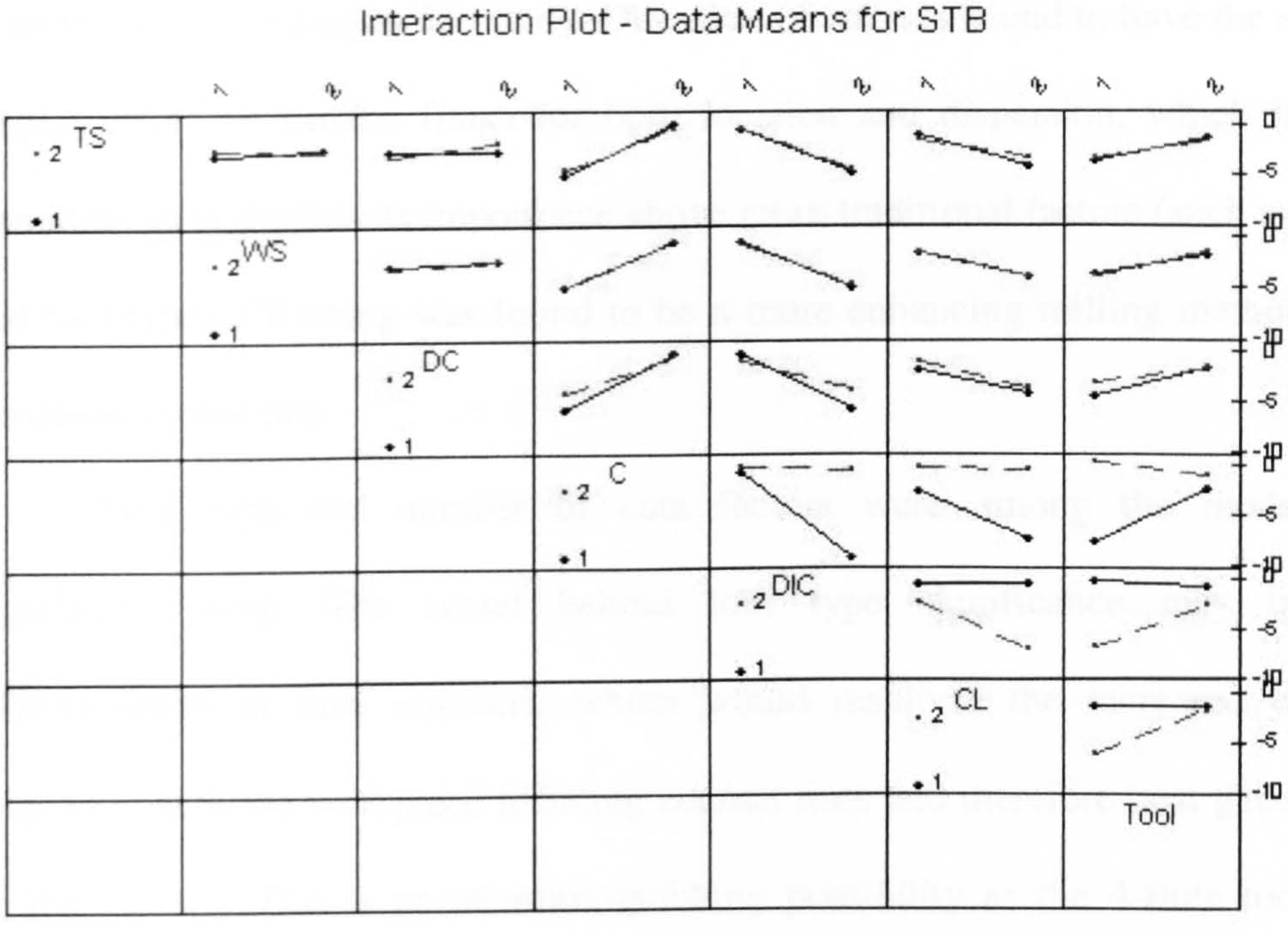


Fig. 3.35 Factor interaction dot-line plot for Signal-to-Noise Ratio (Smaller-The-Better) response (full factorial).

3.5 Discussion

3.5.1 Milling investigation

The study of the different factors affecting surface finish production generated a series of important findings. Outcomes suggested three clear degrees of significance: very significant, moderately significant and non-significant. Factors coolant and direction of cut were found among the very significant group. Coolant, followed very closely by direction of cut, has taken up to two thirds of the total effects on both location and dispersion responses. Indications of coolant significance were expected, as cutting-fluid benefits on surface finish have being pointed out already in the literature (Section 3.2). Therefore, the recommendation of using coolant during machining to relieve temperature effects has been corroborated on this study. On the other hand, the significance of direction of cut is an important finding in this study. Direction of cut was found to have the second largest effect on surface finish for both location and dispersion, which is very important as highlights its importance above more traditional factors (such as feeds and tool type). Climbing was found to be a more enhancing milling method than the conventional one.

Tool type and number of cuts factors were among the moderately significant group. The secret behind tool type significance may be the differentiation in flute numbers, which would result in the increased contact frequency with the workpiece reducing contact time and therefore heat generation on the surface. This is an attention-grabbing possibility as the 4-flute tool was pointed as having a positive effect on surface finish. Interestingly, number of cuts significance may be related to what was described for tool type. However, a simpler explanation for this may be even more feasible. The fact that two-cuts had a better impact than one-cut on surface finish production may indicate that the extra cut could provide a fine cut (removing possible imperfections and rough cuts) and therefore improve the surface finish.

Tool speed, workpiece travel speed and depth of cut were among the non-significant factors group. Lack of importance of tool and workpiece speed may be caused, in part, by closeness on the selection of levels. Machinery is to blame for this, as the speed ranges offered seemed to be not enough for reflecting significant changes and/or improvements. A possible solution for this may be setting more spacing between both choices (more importantly tool speed), which may result in higher incidence of these factors on surface finish. Radulescu et al (1997b) proved a direct relationship between surface roughness variation and rotational speed in experiments considering a selection of tool speed of 2200 and 3800 rev/min, though it was done through theoretical and simulated results.

Results found for the confirmation runs were slightly under par if compared with equivalent settings in the full factorial design. Prediction of better surface roughness through them may be caused by tool and/or workpiece vibration. A visual check of the 4-flute tool showed signs of wear, which may have had serious effects on surface roughness. Another possibility, though unlikely as the design of the CNC machine provides enough stability to prevent these issues, is the presence of vibration in the process. Vibration should not be ruled out at all as Radulescu *et al* (1997b) suggested that the possibility of underlying self-excited vibrations may have certain significance within the process. On the other hand, it is possible that the visible damage on surface and tool (e.g. Built-Up Edges, flank wear) may be caused by combination of slow speeds and tool type.

On the interaction side, there were interesting combinations that may give clues about other issues. Direction of cut proved to be very important for surface finish when combined with higher number of cuts. The most illustrative of the interactions was the 3-way one between coolant, direction of cut and number of cuts, as their best settings combined seem to give a big boost for the production of fine surface finish.

In relation to the investigation of measurement methods, the selection of either method seemed to have no effect on the determination of significant factors as in fact results from both had similar tendencies. Both roughness measurement methods (parallel and perpendicular to direction of tool travel) suggest similar behaviour and performance related to roughness on surfaces. There was a noticeable difference on the actual surface roughness values reported by both, with the parallel measurement method reflecting lower roughness values (Appendix B7). The parallel measurement method does not reduce variation in samples (though smaller values and closer roughness values may give that impression) but it has similar effects on results as Data Transformations may have.

3.5.2 Taguchi approach

Having a look at most Pareto charts (Figs. 3.18 and 3.26), it may be noticed that some significant factors did not match the 10% line or the order of plotting, which may indicate the magnitude and importance of interaction effects on the experiment or a split-plot effect (as indicated by the grouping of TS, WS and DC interactions in those figures). This may be an additional explanation for the lack of significance of factors TS and WS. It may sound like a panacea for most issues found in this study but it may not be known until new clues are given by further investigation (Section 3.6.2).

A proof of the adaptability of the framework methodology is the consistency of results from the first stage and second (final) stage of this study. Aspects like factor significance and array performance were steady throughout the study in a way that results from the first stage may be brought as a "preview" of what can be expected from the final array. It can also contradict to some extent the supposition of being under the effects of a split-plot design, as it may suggest that results could be independent of the blocking array. This may be reinforced by the similar results obtained for both array types in both stages. Outcomes from both full factorial and Taguchi arrays also suggest that Taguchi arrays capabilities for determining significant factors/levels is on par with that from full factorial designs. However, they fail to rank factors in their order of significance as the full factorial does (Fig. 3.25). With factor/level analysis, Taguchi arrays do identify important factors, but not necessarily in right order. Results obtained from Taguchi designs also reflected the high effect of confounding on these exceptionally saturated designs because of the lack of fit shown by ANOVA.

Mixed results obtained for the confirmation runs, especially their poor prediction result capabilities, may have various causes. Notice that the performance gap (between full factorial and Taguchi predictions) was smaller for results in the second stage, which points at a possible reduction of the variability in the second stage, reducing the overall variability as a consequence. This happens to occur regardless of the linear graph utilised, which suggest that this lack of prediction may be caused by the settings selected and not because of the influence linear graphs choice may have on it. This may be a serious criticism to Taguchi's approach because it may reinforce the indications of (what have been claimed in the literature) statistical deficiencies of orthogonal arrays. Results for the confirmation run using SNR should not be considered representative of what confirmation runs can do, as it was influenced by SNR deficiencies which were confirmed in this study. SNR was shown to be strongly correlated to mean rather than dispersion and at the same time its best design settings (which were utilised for the confirmation runs) seemed to be outperformed by those for mean and standard deviation. In addition to this, the variation of SNR values from confirmation runs for equivalent full factorial and Taguchi arrays were really off the pace (with differences of at least 350%), which may be a sign of poor estimation and modelling (of both location and dispersion).

Apart from SNR deficiencies, linear graphs utilised in Taguchi arrays seemed to also have their weak point. Comparing results from confirmation runs of Taguchi arrays and their equivalent full factorial may be misleading, as this tool was not designed for being used with the latter. A proper way is by comparing the results from both linear graphs for the same design settings for the Taguchi array (only). In this way, results were very similar for the first stage, which suggests that the selection of different linear graphs should not affect the final result (ANOVA and GLM results (Tables 3.14) corroborated this). For the final stage of the study the picture was slightly different, as results obtained for confirmation runs were different to each other by a substantial margin. These contradictions may suggest certain unreliability from these tools that should be carefully looked at by the experimenter. Despite all these issues and all the trade-offs, the application and addition of confirmation runs to designed experiments, as suggested by Taguchi, may still pay off. This can be confirmed by looking at the average of all runs (Appendix B7) compared to the result obtained from confirmation runs (Table 3.17) from which can be seen that the latter indicates a better surface roughness index.

3.6 Recommendations

3.6.1 Milling Investigation

The most important issue surrounding the study of significant factors for the milling case study was the lack of significance of the two feed speeds (tool speed and workpiece travel speed). Despite the fact that they have been theoretically suggested (Section 3.2) as important for metal cutting processes, the lack of significance found in this study raises some questions. A few issues have been identified as possible explanations for this, but the most likely one is related to the limitations in the machinery. Based on this, it would be worth suggesting a further investigation in which reassessment of the significance of these two factors can be included. There are two recommended ways of doing this. The first one is by considering a two level experiment design in which level settings are chosen far apart (a wider gap than the one used in this study is highly recommended), cutting machine allowing. If the machinery still limits levels to a narrow gap, a three-level experiment design (or surface response design) for studying curvature effects may be an interesting path to look at. The latter would render a surface for better estimation of the optimal settings and, possibly, for finding clearer signs of significance (for those factors) than those found in this study.

Since the use of simulation environments is becoming more frequent in manufacturing and few attempts have been made for modelling (mathematically) some aspects of milling processes, an interesting area for further study may be the use of a sequential experimental approach for building a model in which surface finish production can be simulated. The model may be enhanced and optimised through (of the sequential experimentation approach) the use of powerful optimisation techniques, such as Genetic Algorithms, and reinforced by more complex AI technologies, such as Neural Networks, for modelling, rendering and controlling the production and movement of swarf during machining.

3.6.2 Taguchi approach

The fact that there is a possibility for split-plot effects affecting the results, suggests a further (re)examination of the data obtained in this study from the perspective of a split-plot design. Therefore, a thorough investigation to assess the effects these types of design may have on the experimentation strategies and the set of statistical tools (Taguchi and non-Taguchi) might bring more light that may complement the present study.

Chapter 4

Traffic Flow Simulator Case study

4.1 Objectives

Travel time prediction is one of the objectives of the study of traffic flow which aims to improve services offered by transport companies by having timetables that are more accurate. Successful applications of this can be found in public transport, especially in very congested cities such as London where prediction of travel time has optimised transport operations. Traffic flow simulators, like the one used in this work, VISSIM (PTV, 1999), have been used to evaluate traffic operations in a combined network of coordinated and actuated traffic signals, as well as to evaluate the impact of integrating light rail into urban street networks (PTV, 1999). Modelling road traffic in detail to optimize traffic flow may enable traffic situations to be improved without constructing new road infrastructure (Fellendorf and Vortisch, 1999). Since traffic flow models like VISSIM show a great level of detail, they are focused on simulation at the operational level, allowing in principle comparisons of various intersection layouts, including stop-sign controlled intersections, roundabouts, signalised intersections, etc (PTV, 1999).

This case study, with the complexity of this simulation system very close to real physical experimentation, can be a challenge for the application of Taguchi tools. Though this is not the only case study where Taguchi methods have been applied to computer experiments (eg Belavendram, 1992), Belavendram's research was focused on small-sized computer experiments. The study of the implementation of DoE through Taguchi tools into large sized computer experiments is the aim in this case study. This can be achieved through the following objectives:

- Determine factor and level significance for the traffic flow simulator as the first step to achieve simplification of simulator set up activities.
- Verify the compliance of Taguchi tools with large sized computer experiments.
- Establish comparisons between standard DoE and Taguchi tool outcomes and their impact on the use of simulations for testing.
- Estimate potential benefits and drawbacks found in the application of these tools to computer experiments.

Simulations required in this case study were carried out by members of the Transport Operations Research Group of Newcastle University during the period 1997-1998. The application of DoE and Taguchi tools was seen as an interesting research possibility within the series of activities carried out by that group. Therefore, this case study focused on the improvement of the factor-selection process and the setting of simulator input parameters that may enhance and optimise overall responses.

One contribution of this present study to the transport research, was to suggest that user (driver) satisfaction might be related not only to mean travel time but also to the variability in that, in exactly the same way that variation is a problem in manufacturing processes.

4.2 Background to the case study

VISSIM (PTV, 1999) is a simulation model program that can analyse traffic and transit operations. It contains a sophisticated simulation model that allows the user to analyse accurately complex traffic operations as well as traffic/transit interactions (PTV, 1999). VISSIM can be used to evaluate and compare various intersection layouts including roundabouts, stop sign controlled and signalised intersections, and grade separations with interchanges. It represents an extreme (at the current technological level) of the type of software that might potentially represent materials flow within a manufacturing process. Most of its features are beyond the scope of this work. However, mentioning some of these features will help understanding to some extent of its functionality and facilities.

The model implemented in VISSIM (Klein and Mills, 1994; Fellendorf, 1994) is based on the work of Wiedemann (1991), which contains a psycho-physical car following model for longitudinal vehicle movement and a rule-based algorithm for lateral movements (lane changing) (PTV, 1999). The traffic flow model is a discrete, stochastic and time-step based model with driver-vehicle-units as single entities (PTV, 1997). The simulation is microscopic (single vehicle modelling) and stochastic with fixed-slices (1 second intervals) (PTV, 1997). Car-following and lane-changing together form the traffic flow model, being the kernel of VISSIM (PTV, 1997). The kernel requires certain parameters, such as network geometry, in order to build the model. Network geometry is the basic specified element, ie the layout and geometry representing single or multiple lane roadway segments (PTV, 1997). These can be modelled using VISSIM's graphical interface, generally based on a scanned layout plan of the modelled network as a background (Fig. 4.1). A network is created by connecting multiple links, which can be designated to control other model parameters (PTV, 1997). Additional specified model parameters are traffic volumes and the vehicle fleet. In addition, it is possible to define other parameters specific to vehicles (i.e. vehicle types, or sets of vehicles) and drivers, as well as different distributions of desired speeds (PTV, 1997).

The result of the simulation is an animation of the traffic flow together with reports of travel time and waiting time distributions, which were the data generated and used for this experiment. Offline reports are a number of files written during simulation, using standard text formats. The animation part of VISSIM is displayed on screen similar to a Flash (Macromedia, 1999) multimedia animation, where vehicle movements are shown in detail for the length of the simulation. Travel time is calculated, which is the delay within a certain network segment. Segments for calculations are set within model parameters (PTV, 1997).

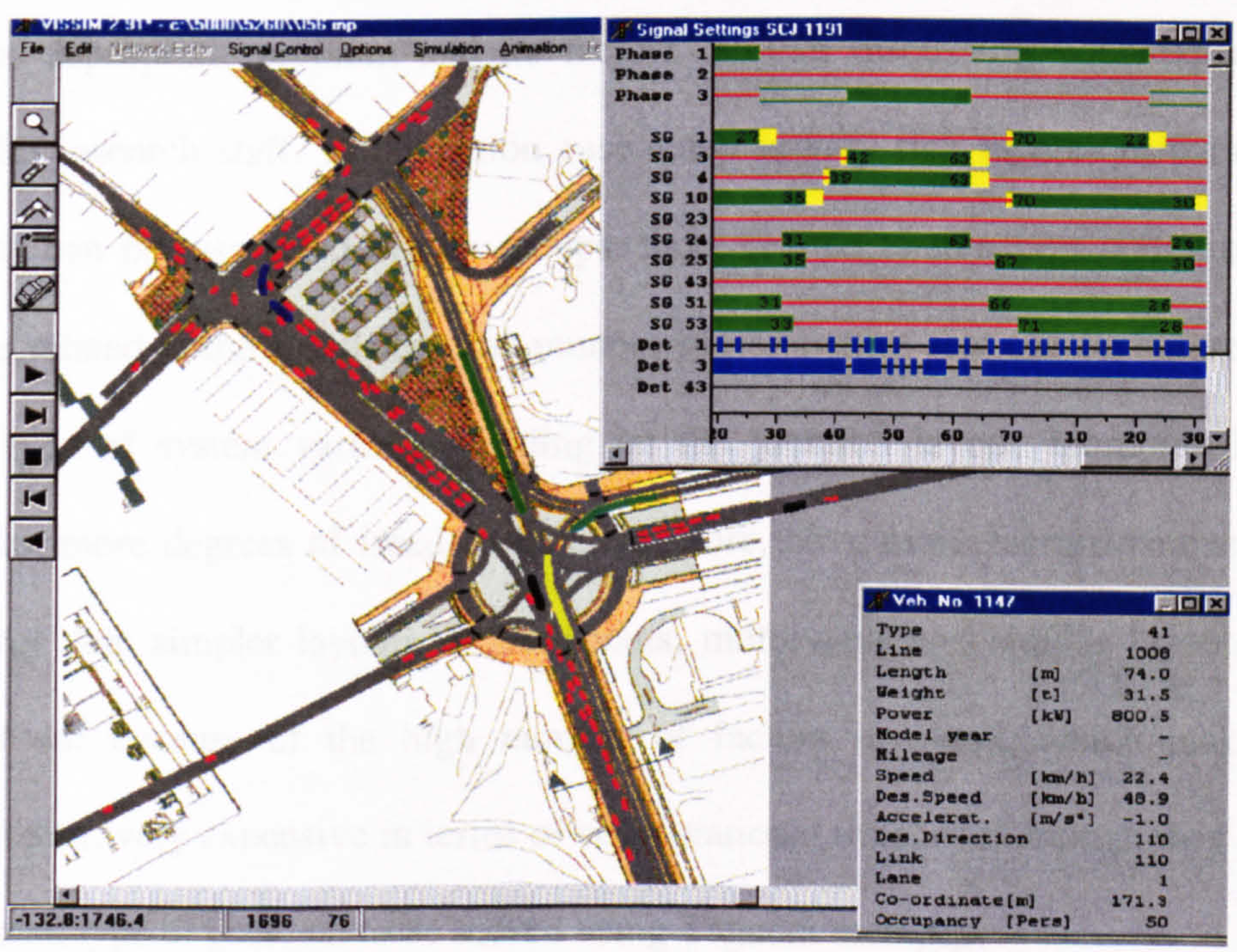


Fig. 4.1 Screenshot showing VISSIM's graphical interface, animations and modelled network layout (Fellendorf and Vortisch, 1999)

4.3 Three-leg continental junction case study

4.3.1 Experimental design phase

Following the suggested framework (Section 3.1), problem definition is similar to that from the metal cutting experiment with some variations related to the different nature of this case study. One of the purposes of studying traffic is to predict accurately travel time. Simulators are complex systems which require tuning in order to get the most of them. This traffic simulator is not an exception, making it a good choice for this case study where investigations can be focused on using DoE to reduce time spent on "tweaking" system parameters needed to obtain the preferred response (e.g. travel time) as well as to enhance and/or optimise the effect of the response.

In this case study it was possible to draw on previous brainstorming and junction simulation processes within TORG which had led to a good knowledge of the factors affecting the problem. "Brainstorming" in this case focused on selection of an appropriate problem and its factors through discussion with experienced TORG research staff. The junction case study is very rich in options/parameters which can be associated in two groups: those related to transport operations and those related to the simulator. The number of parameters that can be controlled in this type of system varies depending on the junction layout. Complex layouts require more degrees of freedom and, therefore, have more factors/parameters to control than simpler layouts. Roundabouts, motorways and similar layouts were ruled out because of the high number of factors involved, which makes the simulation very expensive in terms of computational time, even though they can be the ideal type of problem to be solved using Taguchi methods.

The object of study was a fully signalised 3-leg continental junction, also known as a T-junction, which is one of the simplest types. Factors such as signalisation, number of carriageways and road system are involved within the layout definition. Signalisation is a factor that can be studied at different levels depending on the different degrees of signalisation (e.g. full, partial and no signalisation). The number of lanes affects road capacity and therefore traffic flow. Road system refers to left (British) or right-hand (continental) side drive. There are other factors related to vehicle flow control, such as saturation flow, controller type and vehicle mix. Saturation flow is the design volume capacity of any segment and vehicle mix is the combination of different vehicle types passing through the controllers at a certain rate. Common controllers are traffic lights, which can have as levels different control algorithms and the factors (green time, red time, etc) associated with these. The other group of factors, those related to the simulation system (core and model), are control variables for generating and managing behaviour patterns for vehicles and controllers. For instance, the model works with different time profiles in the form of distributions, such as speed and magnitude, so different conditions of traffic flow can be studied (eg rush hour, etc.).

Response selection for this case study can be aimed at the most common application, which is travel time prediction. Travel time records the average travel time for all vehicles between two points in the network over the recording interval which is preset before the simulation run (PTV, 1997). Travel time is inclusive of all delays including stops at red lights, stops by buses and stops by Light Rail Transit (LRT) at stations. Travel time is not the only possibility. Other important responses, which are associated with travel time, are delay and green times. Delay within a certain segment of the network is recorded like travel time. Studying delay times identifies potential areas/sectors affecting traffic flow and therefore travel time. Traffic flow studies can be directed at optimising green time instead. This option can be important when studying complex junctions as maximising green time will undoubtedly improve travel time for a given segment. Depending on the object of study and on other factors to be studied, green time can be seen as either a response or a factor (if fixed time controllers are used).

Reduction of the number of factors to be studied to an acceptable minimum follows. Key factors, such as controller type and vehicle mix, were kept. The remaining factors selected were system factors. The need to study the effects of different probability and speed distributions on total delay suggested analysis of different distribution profiles for the three arms of the T-junction (ie traffic loading increasing/decreasing with time). Three profile slopes were selected as independent factors, one for each leg. These profiles can have two shapes, either increasing frequency with time (up) or decreasing it (down), which are the levels to be considered for this factor. Similarly, three profile magnitudes were selected as factors (one for each leg). The idea is to represent how busy the junction is going to get on particular days of the week. For instance, a profile can represent a weekday that is expected to be busier than on a weekend. Also, if desired, profiles can be set to frequencies specific to particular days of either weekdays or weekends. In this case levels for each one of the profiles are going to be considered as weekdays (level 2) and one particular day, Sundays (level 1). Because these six profiles have identical settings, in order to differentiate factors for the effects of the study, they will be numbered following labels for each one of the junction legs (Fig. 4.2).

Defining the system to study a fully signalised 3-leg continental junction also reduced some of the factors to single level (signalisation, number of carriageways and road system). Controller type was selected as it has been considered as very important. "Traffic responsive" (those traffic lights that allow interactions from pedestrians as well as interactions from traffic sensors on the road to estimate green time) and "fixed time" (common traffic lights with predetermined green time) are the most common ones in urban areas and were used as levels for the controller type factor. Vehicle mix was chosen because of the incidence in traffic flow of heavy vehicles such as buses, trucks and Heavy Goods Vehicles (HGV). In this case, levels were set depending on the proportion of HGV in the total vehicle flow (low and high). The low value should not be too low because of the pseudo-permanent presence of public transport in urban areas. On the other hand, higher values of vehicle mix should not be greater than 25% as it would not be a real case, except in an industrial estate.

Speed distribution is important to study the effects of vehicle incoming-speed into the junction, establishing possible differences between small and large ranges of speed. These ranges should not be at high speed because vehicles should be approaching a junction at a reasonably slow speed. Thus even the large range should not comprise a difference bigger than 20km/hr.

One reason for the choice of this case study in the Taguchi context is that there is a possibility of finding interactions among some factors because of their close relationship. For instance, factors related to the model-simulator such as profiles and speed distributions may interact because of the probabilistic nature of the model. In addition, the combination of other factors such as saturation flow and vehicle mix regulates vehicle flow into the system. This likelihood identifies a need for an experimental design to locate interactions so as to test the ability of Taguchi techniques to cope with such problems. At the same time, the chosen experimental design should be compatible with previous designs in order to allow comparisons. A full factorial array was the main design choice, so there are enough degrees of freedom to handle interactions. A Taguchi design composed of data extracted from the full factorial design was chosen to test its ability to cope with these types of problems. Fractional factorial designs could have been chosen instead of the large and expensive full factorial, but would not offer the type of comparison wanted in this work where the idea is to "benchmark" simpler fractional factorial designs, such as Taguchi's, against complete and standard full factorial designs.

The selection of these nine factors (Table 4.1) gives final shape to the experimental arrays. The 2-level full factorial array is now 2^9, which is equivalent to 512 runs. Runs were performed in two fully randomised blocks of 256 runs each, using controller type as a blocking factor. The Taguchi array, an L_{32}, should be composed of runs, with identical set up to those in the full factorial, extracted from the full factorial array (Section 3.4). There are only 31 degrees of freedom available for estimation in this Taguchi design where interactions are confounded with main effects. Allocation of main factors to the different columns was done through the use of linear graphs. There are thirteen different types/shapes of linear graph for this Taguchi array (L_{32}) with the maximum number of main factors that can be studied without confounding ranging from 12 to 20. The linear graph utilised in this case study (Fig. 4.3) allows a maximum of 12 main factors that can be allocated in the Taguchi array, leaving the remaining columns (three) available for error terms. Notice that unlike the metal cutting case study, only one linear graph was utilised in this traffic flow case study.

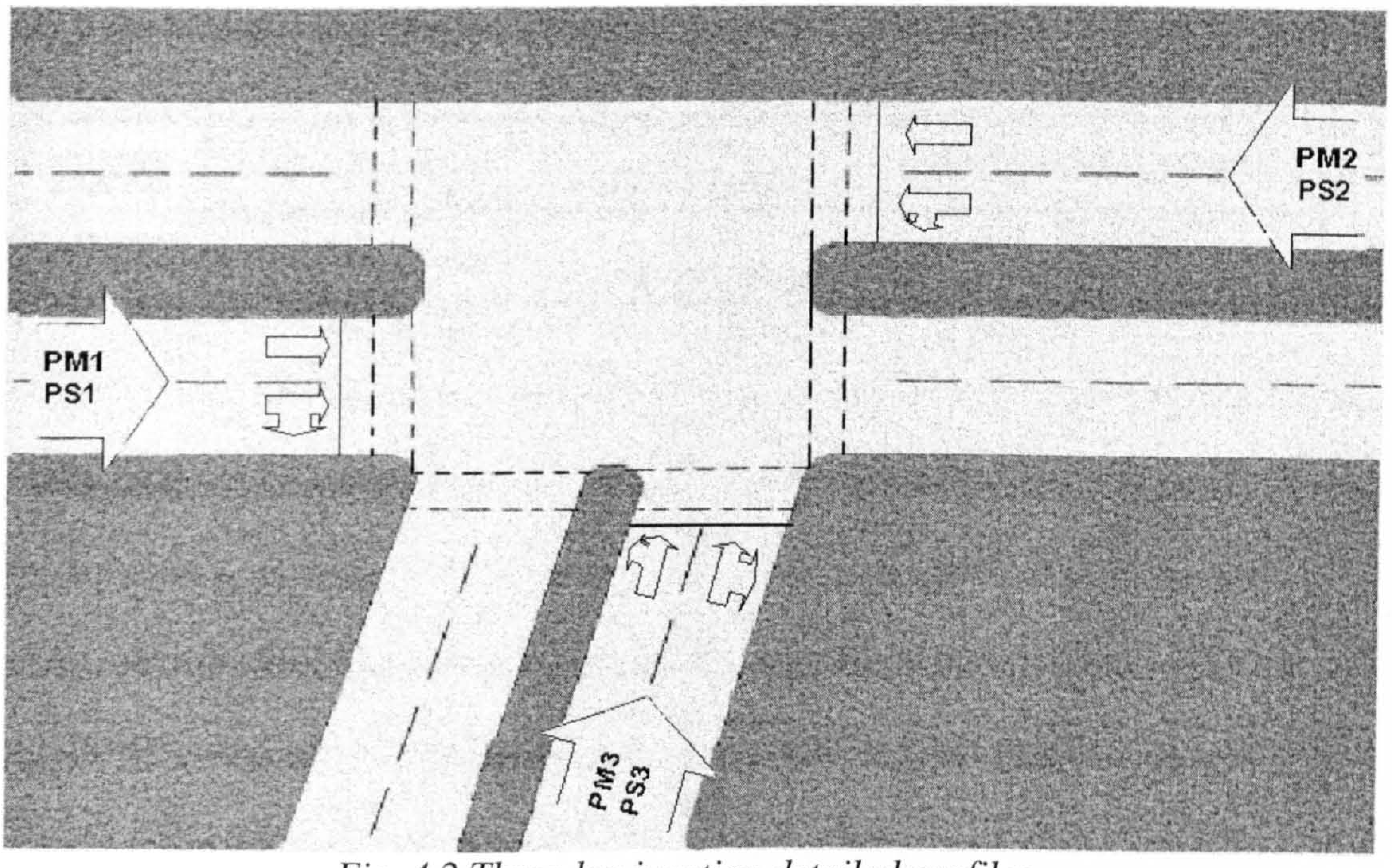


Fig. 4.2 Three-leg junction detailed profiles.

Label	Factor	Level 1	Level 2
CP	Controller Type	Vehicle/Traffic Responsive	Fixed Time
VM	Vehicle Mix	Low (5% HGV)	High (20% HGV)
SD	Speed Distribution	Small Range (48-52 km/hr)	Large Range (40-60 km/hr)
PS1	Profile 1 Slope	Increasing volume	Decreasing volume
PS2	Profile 2 Slope	Increasing volume	Decreasing volume
PS3	Profile 3 Slope	Increasing volume	Decreasing volume
PM1	Profile 1 Magnitude	Sunday (100-500 veh/hr)	Weekday (300-1000 veh/hr)
PM2	Profile 2 Magnitude	Sunday (100-500 veh/hr)	Weekday (300-1000 veh/hr)
PM3	Profile 3 Magnitude	Sunday (100-500 veh/hr)	Weekday (300-1000 veh/hr)

Table 4.1 Summary of factors and levels for the 3-leg junction case study.

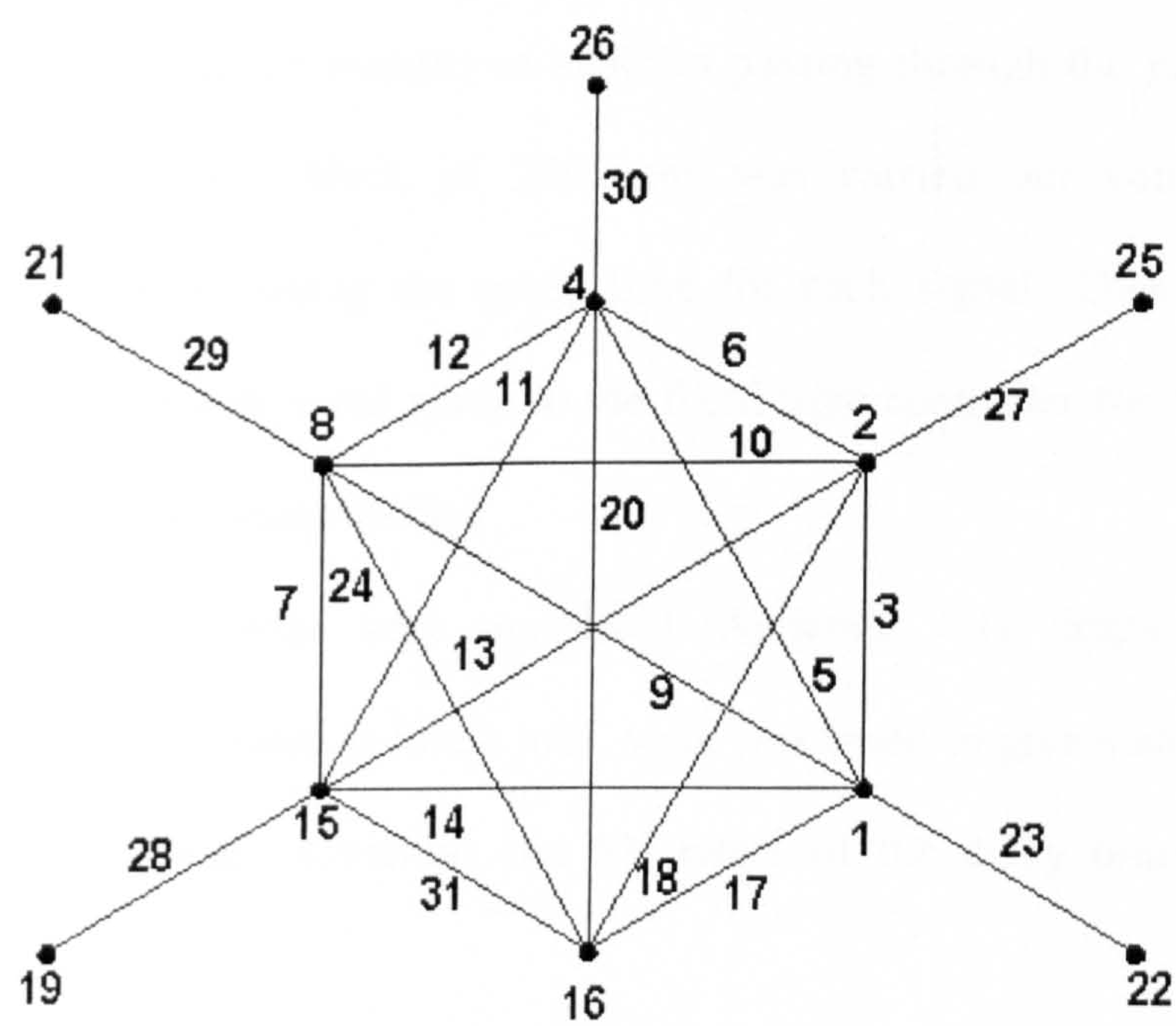


Fig. 4.3 Linear Graph selection for the L_{32} array (from Peace, 1993).

4.3.2 Data Acquisition phase

The experiment started with the preliminary task of setting up parameters in the simulator. The simulator requires flow profiles to be created spanning a total period of two hours, using ten-minute time-slices. Then, it is necessary to produce a list of random numbers (seeds) which are used to randomly create initial conditions, set up appropriate input files for the simulator (factor/level settings), create batch files to enable jobs to be run off-line and, finally, to automate processing of output files. Each experiment (run) was replicated eight times, by selecting (randomly) a different random seed for each replication. Replication of the experiment was integrated into the batch job, so the eight repetitions were done before continuing with the next run.

VISSIM (PTV, 1999) version 2.30 was used to output time-series of delay of vehicles, as well as the number of vehicles passing through the junction under investigation. The first block of 256 runs was carried out with the traffic responsive controller, noting the green time for each signal. Then the average green time was calculated and given to the fixed time controller for second set of runs to ensure direct comparability.

Once the 512 runs were completed (Appendix C1), output time-series, contained in files generated in batch jobs, were processed to give statistics such as mean, median, standard deviation and SN ratios of the delay time. Mean was calculated using:

$$Mean = \frac{\sum_{i=1}^{8} D_i V_i}{\sum_{i=1}^{8} V_i} \tag{4.1}$$

where: i = replication

D_i = Delay time for replication i.

V_i = Number of vehicles for replication i.

Remaining statistics, such as standard deviation, median and SNR (smaller-the-better), were calculated from the average delays obtained in each run. All calculations were done using eight repetitions. It is known that SN ratios were originally conceived to be used (ideally) with Taguchi arrays only, though the concept of dealing with both location and dispersion effects is wide enough to be applied in other models. Data organisation for the Taguchi array (Appendix C2) consisted of searching in the full factorial array for equivalent runs defined in the Taguchi array with identical set up (excluding interaction columns). The whole row including parameters and data is extracted from the full factorial array, so no further calculations are needed.

4.3.3 Data analysis phase

Analyses were focused on determining factor significance, optimal factor/level settings to enhance (reduce) delay time, as well as carrying out the parallel investigation on Taguchi tools. Analyses were carried out on the full factorial design in the first instance using the whole data set of 512 runs, followed by those based on the Taguchi design. Firstly, a correlation test was carried out to determine possible linear dependencies and/or relationships among factors (Table 4.2) and responses (Table 4.3). The factors were proved to be independent of each other. On the other hand, there was a direct correlation between mean and median (as expected), as well as an inverse correlation between mean and SNR (and therefore with median). SNR was only weakly correlated with standard deviation.

Similar results were obtained for correlation for both designs, which suggests it is present between the responses regardless of the experimental design utilised. The median has been used just for comparison purposes as a reference guide for the test as it is generally expected to be correlated to the mean under certain conditions (Grove and Davis, 1992). Thereafter, median was not used as a response.

Keeping in mind this set of correlations among responses, an ANOVA test was carried out for each one of the responses in the study (mean, standard deviation and SNR) in order to gather more information. The original idea was to perform the analyses considering third-order interactions in the model. However, this was not possible due to software limitations (Minitab (1998) can handle up to 127 terms only), so only second-order interactions were studied. At the same time, the drawback of this software limitation is that one of the few possibilities available (using simple tools) for studying third-order interactions, through Pareto charts, was unfeasible. Model suitability was nearly perfect for the GLM version of each one of the three responses using both full factorial and Taguchi arrays (probability of accepting the hypothesis was 0.000 for some responses) (Table 4.4). These values for model suitability had uniform and consistent results for both full factorial (main and interaction effect) and Taguchi (main effects only) arrays for main effects only. Results from the ANOVA tests were put together with an overview of main factors and interactions plots into a summary table (Table 4.5) for easing the process of determining factor significance. Six main factors (VM, PS1, PM1, PM2, PM3 and CP) were found significant among the main factors for the three responses in the full factorial array. Factor PS3 was also found significant for both mean and SNR but had no effect on dispersion. Only one interaction

(PM3*CP) was found significant for the three responses at the same time. Nine interactions (VM*PM1, VM*PM3, VM*CP, PS3*PM3, PS3*CP, PM1*PM3, PM1*CP, PM2*PM3 and PM3*CP) were found significant for both mean and SNR, three (PM2*CP and VM*PS3) significant for mean only and three (SD*PS1, SD*PS2, PS1*PS2, PS1*CP) for standard deviation only. None of the interactions involved non-significant factors.

ANOVA results for the Taguchi array were slightly different than those found for the full factorial array despite a good model-fitting (Table 4.4). These differences are reflected on the reduction in number of the significant main factors (for the three responses) for the Taguchi array (when compared to those in the full factorial array) which went down to only two (PM3 and CP). Two other factors (PM1 and PM2) were found to have an effect on dispersion and SNR, as well as factor VM which had an effect on both location and SNR. In the interaction field, only three interactions showed signs of significance. Interactions PS1*PM1 (affecting only location), VM*CP (affecting both location and dispersion) and VM*SD (affecting location and SNR) were the only significant ones, with the one between VM and CP being found significant for the full factorial array too. This may mean that despite the known issue surrounding Taguchi's way of dealing with interactions (Section 2.4), determination of some significant effects can be (coincidentally) comparable to those obtained for the full factorial array.

Similarly, looking at dot-line plots, which are also helpful for determining the best combination of factors and levels, visual evidence indicated how closely (sometimes identically) Taguchi arrays performed in comparison to full factorial arrays for the three responses. For mean and SNR responses (full factorial) (Figs.

4.4 and 4.6) a best setting was identified with low vehicle mix, small range speed distribution, increasing slope profiles, Sunday type profile magnitudes (1 and 3), weekdays type profile magnitude (2) and traffic responsive controller type. The only difference between this selection for the full factorial array and that one suggested by Taguchi array is the preference for a decreasing profile slope instead.

Dot-line plots for dispersion effects (Fig. 4.5) were slightly different if compared with location effects. Best design settings for the full factorial array should include the use of high vehicle mix, small range speed distribution, increasing slope profiles, Sunday type profile magnitudes and fixed time controller type. Results obtained with the Taguchi array, however, suggested opposite settings (to those for the full factorial) for vehicle mix, speed distribution and one of the profile slopes (2). This may imply that while Taguchi arrays are acceptable for determining the best combination for means, they may not be so effective for dispersion.

Interaction dot-line plots (Figs. 4.7 to 4.9) did not suggest other interactions not found in the ANOVA test. Most plots were parallel/overlapping lines, which makes it very difficult to spot differences or may simply indicate non-significance. Pareto charts (Fig. 4.10) may play a part in determining significant interactions not found with ANOVA. Similarities between both array types for the three responses are present again in these charts. However, no further differences were found as all charts pointed at those results suggested by ANOVA (as expected). These charts also indicated that the effects dispersion has on delay time are mostly dominated by profile magnitudes and controller type.

Rank order for influence of main factors on mean (location), standard deviation (dispersion) and SNR responses was plotted based on the F-values from the GLM tests (Fig. 4.11). Estimation of these effects was done considering the individual contributions on the main factors total.

	SD	PS1	PS2	PS3	PM1	PM2	PM3	CT
VM	0	0	0	0	0	0	0	0
SD		0	0	0	0	0	0	0
PS1			0	0	0	0	0	0
PS2				0	0	0	0	0
PS3					0	0	0	0
PM1						0	0	0
PM2							0	0
PM3								0

Table 4.2 Correlation (Pearson) matrix for main factors.

	Full factorial design			**Taguchi array**		
	Mean	**Std. Deviation**	**SNR**	**Mean**	**Std. Deviation**	**SNR**
Std. Deviation	0.117			0.027		
SNR	-0.976	-0.165		-0.979	-0.051	
Median	0.996	0.107	-0.966	0.995	0.007	-0.965

Table 4.3 Correlation (Pearson) matrix for main responses – full factorial and Taguchi arrays (original data from appendixes C1 and C2, respectively).

		Source	DF	Seq SS	Adj SS	Adj MS	F	p>F
Mean	Full Factorial	Main Effects	9	32862	32862	3651.34	427.07	0
		2-Way Interactions	36	13741	13741	381.69	44.64	0
		Residual Error	466	3984	3984	8.55		
		Total	511	50587				
	Taguchi	Main Effects	9	2607.47	2607.47	289.72	12.61	0.013
		2-Way Interactions	18	1053.02	1053.02	58.5	2.55	0.189
		Residual Error	4	91.9	91.9	22.98		
		Total	31	3752.4				
Standard Deviation	Full Factorial	Main Effects	9	15133414	15133414	1681490	1.00E+03	0
		2-Way Interactions	36	64040	64040	1779	1.48	0.04
		Residual Error	466	561754	561754	1205		
		Total	511	50587				
	Taguchi	Main Effects	9	968342	968342	107594	300.1	0
		2-Way Interactions	18	7932	7932	441	1.23	0.467
		Residual Error	4	1434	1434	359		
		Total	31	977708				
Smaller-the-Better	Full Factorial	Main Effects	9	4590.5	4590.5	510.061	728.11	0
		2-Way Interactions	36	1182.9	1182.9	32.857	46.9	0
		Residual Error	466	326.4	326.4	0.701		
		Total	511	6099.8				
	Taguchi	Main Effects	9	342.52	342.52	38.058	17.78	0.007
		2-Way Interactions	18	88.918	88.918	4.94	2.31	0.217
		Residual Error	4	8.563	8.563	2.141		
		Total	31	440				

Table 4.4 ANOVA model fitting test for all responses on full factorial and Taguchi arrays (traffic flow study) (original data from appendixes C1 and C2, respectively).

		Mean		Std. Deviation		SNR	
		F	p>F	F	p>F	F	p>F
Main Factors	VM	777.26	0.000	12.81	0.000	1046.32	0.000
	SD	0.23	0.631	0.01	0.911	2.48	0.116
	PS1	5.46	0.020	4.58	0.033	10.09	0.002
	PS2	0.17	0.676	1.72	0.190	1.37	0.242
	PS3	77.53	0.000	0.52	0.472	51.09	0.000
	PM1	319.68	0.000	5619.19	0.000	728.73	0.000
	PM2	48.80	0.000	6896.14	0.000	82.65	0.000
	PM3	982.54	0.000	517.26	0.000	1518.09	0.000
	CP	1568.83	0.000	29.20	0.000	2429.25	0.000
Interactions	VM*SD	0.00	0.958	0.04	0.841	0.03	0.865
	VM*PS1	0.72	0.396	0.20	0.653	0.05	0.817
	VM*PS2	0.23	0.631	0.36	0.550	0.60	0.441
	VM*PS3	22.75	0.000	0.12	0.730	2.80	0.095
	VM*PM1	50.00	0.000	2.24	0.135	56.06	0.000
	VM*PM2	2.57	0.110	0.01	0.907	0.07	0.787
	VM*PM3	214.56	0.000	2.02	0.156	107.23	0.000
	VM*CP	375.42	0.000	1.45	0.228	245.48	0.000
	SD*PS1	0.03	0.863	3.87	0.050	0.02	0.896
	SD*PS2	0.03	0.855	4.00	0.046	0.45	0.502
	SD*PS3	0.83	0.364	2.90	0.089	1.52	0.218
	SD*PM1	0.03	0.870	3.04	0.082	0.19	0.666
	SD*PM2	0.00	0.979	0.13	0.721	0.05	0.817
	SD*PM3	0.08	0.772	0.37	0.541	0.14	0.711
	SD*CP	0.00	0.963	0.70	0.404	0.00	0.944
	PS1*PS2	1.30	0.255	5.26	0.022	1.78	0.183
	PS1*PS3	1.46	0.228	0.03	0.871	3.90	0.049
	PS1*PM1	0.00	0.990	0.05	0.825	0.19	0.666
	PS1*PM2	0.02	0.901	1.41	0.236	0.00	0.976
	PS1*PM3	0.75	0.388	0.23	0.633	0.14	0.711
	PS1*CP	3.11	0.078	5.17	0.023	3.74	0.054
	PS2*PS3	0.68	0.411	0.03	0.872	2.06	0.152
	PS2*PM1	0.03	0.860	0.25	0.618	0.19	0.666
	PS2*PM2	0.62	0.432	0.07	0.792	0.60	0.441
	PS2*PM3	0.08	0.780	1.90	0.169	0.05	0.817
	PS2*CP	0.06	0.812	2.97	0.086	0.54	0.464
	PS3*PM1	1.82	0.179	1.43	0.232	2.80	0.095
	PS3*PM2	0.49	0.485	2.27	0.133	0.00	0.944
	PS3*PM3	76.92	0.000	0.92	0.339	59.10	0.000
	PS3*CP	70.90	0.000	1.22	0.269	51.65	0.000
	PM1*PM2	0.26	0.613	0.39	0.534	0.28	0.595
	PM1*PM3	8.87	0.003	0.10	0.747	63.19	0.000
	PM1*CP	78.68	0.000	0.00	0.963	92.02	0.000
	PM2*PM3	16.87	0.000	2.03	0.155	15.52	0.000
	PM2*CP	6.93	0.009	2.15	0.144	0.00	0.976
	PM3*CP	650.29	0.000	3.88	0.049	767.11	0.000
Error		4010.4		540834		360.77	

Table 4.5 Summary of analysis for the full factorial array (traffic flow) (original data from appendix C1).

		Mean		Std. Deviation		SNR	
		F	p>F	F	p>F	F	p>F
Main Factors	VM	19.75	0.007	0.05	0.833	26.07	0.004
	SD	5.24	0.071	5.24	0.071	2.17	0.201
	PS1	0.01	0.936	2.77	0.157	0	0.966
	PS2	0.14	0.724	0.1	0.767	0.34	0.583
	PS3	3.42	0.124	4.45	0.089	3.59	0.117
	PM1	4.03	0.101	1529.53	0	14.05	0.013
	PM2	4.16	0.097	1653.32	0	12.53	0.017
	PM3	33.84	0.002	194.45	0	52.74	0.001
	CP	47.85	0.001	14.92	0.012	76.47	0
Interactions	VM*SD	23.12	0.005	5.1	0.073	29.41	0.003
	VM*PS1	1.04	0.354	0.64	0.46	2.68	0.162
	VM*PS2	0.31	0.6	0.08	0.792	0.34	0.586
	VM*PS3	0.25	0.636	0.25	0.636	0	0.968
	VM*PM1	0.9	0.388	1.87	0.23	0.94	0.377
	VM*CP	9.74	0.026	7.73	0.039	6.11	0.056
	SD*PS1	0.21	0.663	1.39	0.291	0.5	0.511
	SD*PS2	0.96	0.373	1.76	0.242	1.04	0.354
	SD*PS3	0.01	0.944	3.64	0.115	0.14	0.728
	SD*PM1	0.01	0.937	0.09	0.77	0	0.96
	PS1*PS2	1.55	0.268	1.48	0.279	1.18	0.328
	PS1*PS3	0.01	0.946	0.05	0.833	0.12	0.742
	PS1*PM1	7.54	0.041	0.06	0.82	4.96	0.077
	PS2*PM1	0.2	0.675	1.77	0.241	0	0.988
	PS2*PM3	0.02	0.882	0.19	0.678	0.02	0.901
	PS3*PM1	0.21	0.664	1.54	0.269	0.19	0.684
	PS3*PM2	0.93	0.38	0.28	0.62	0.88	0.391
Error		110.09		1422		9.111	

Table 4.6 Summary of analysis for the Taguchi array (traffic flow) (original data from appendix C2).

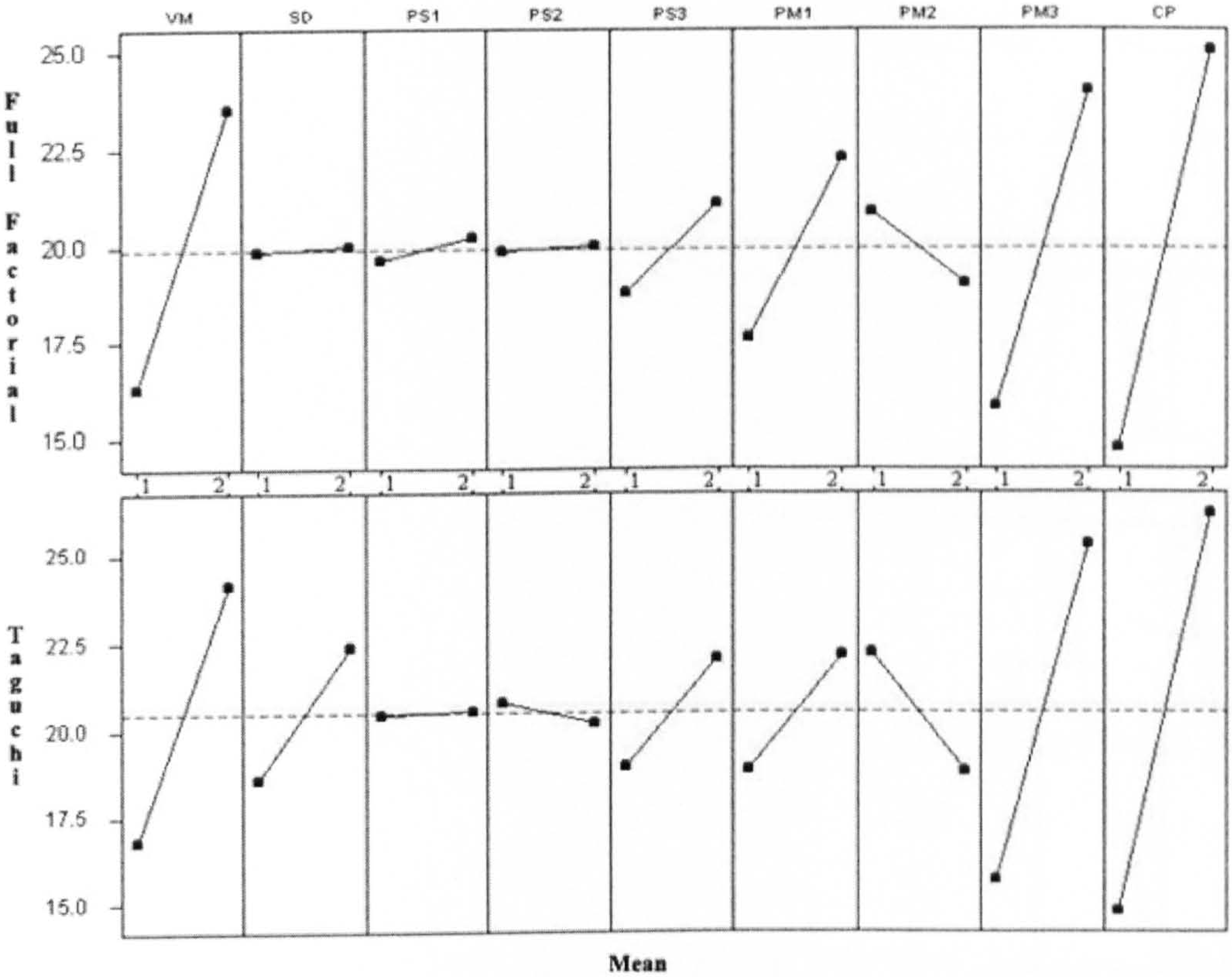


Fig. 4.4 Main effects plot for Mean response (traffic flow).

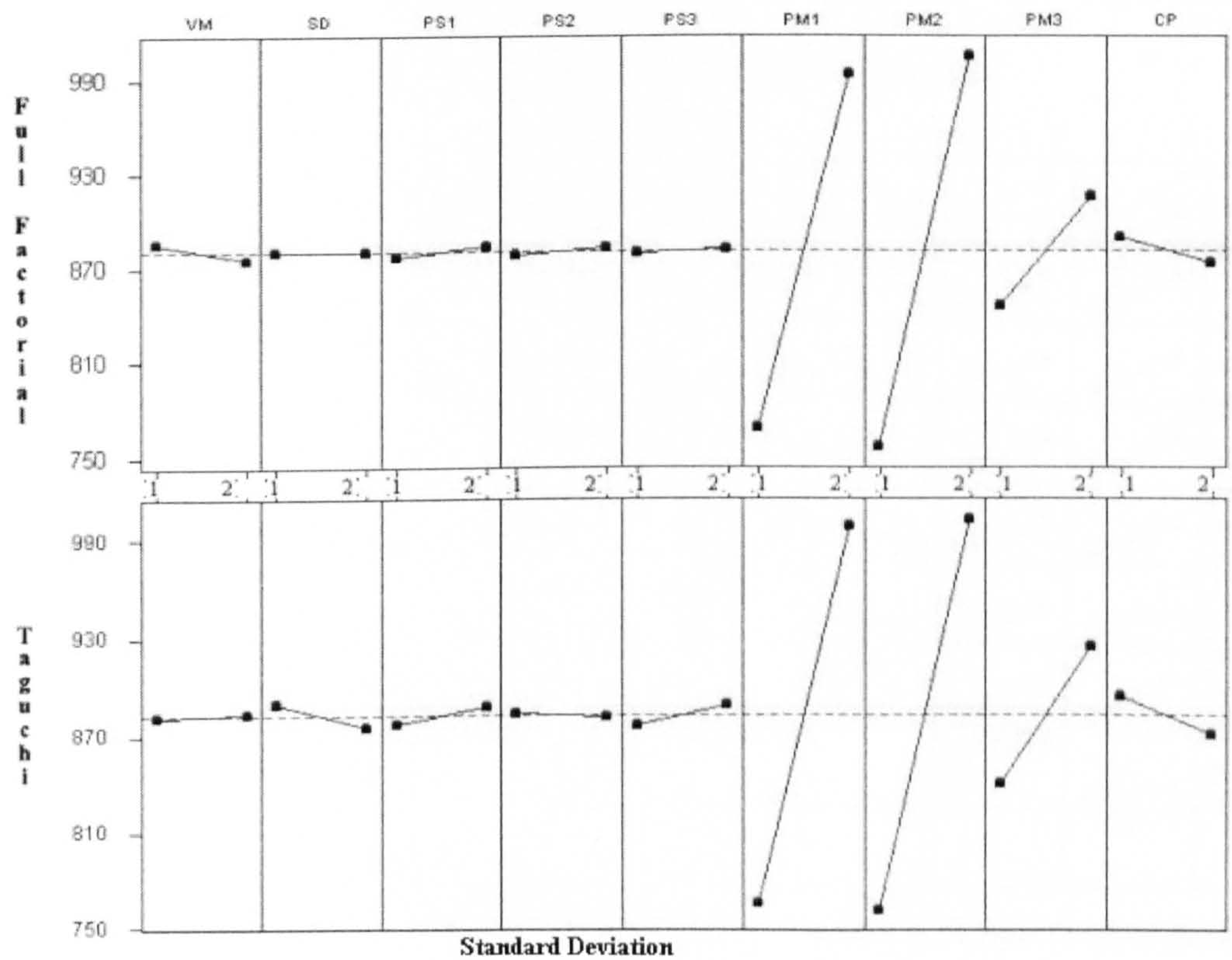


Fig. 4.5 Main effects plot for Standard Deviation response (traffic flow).

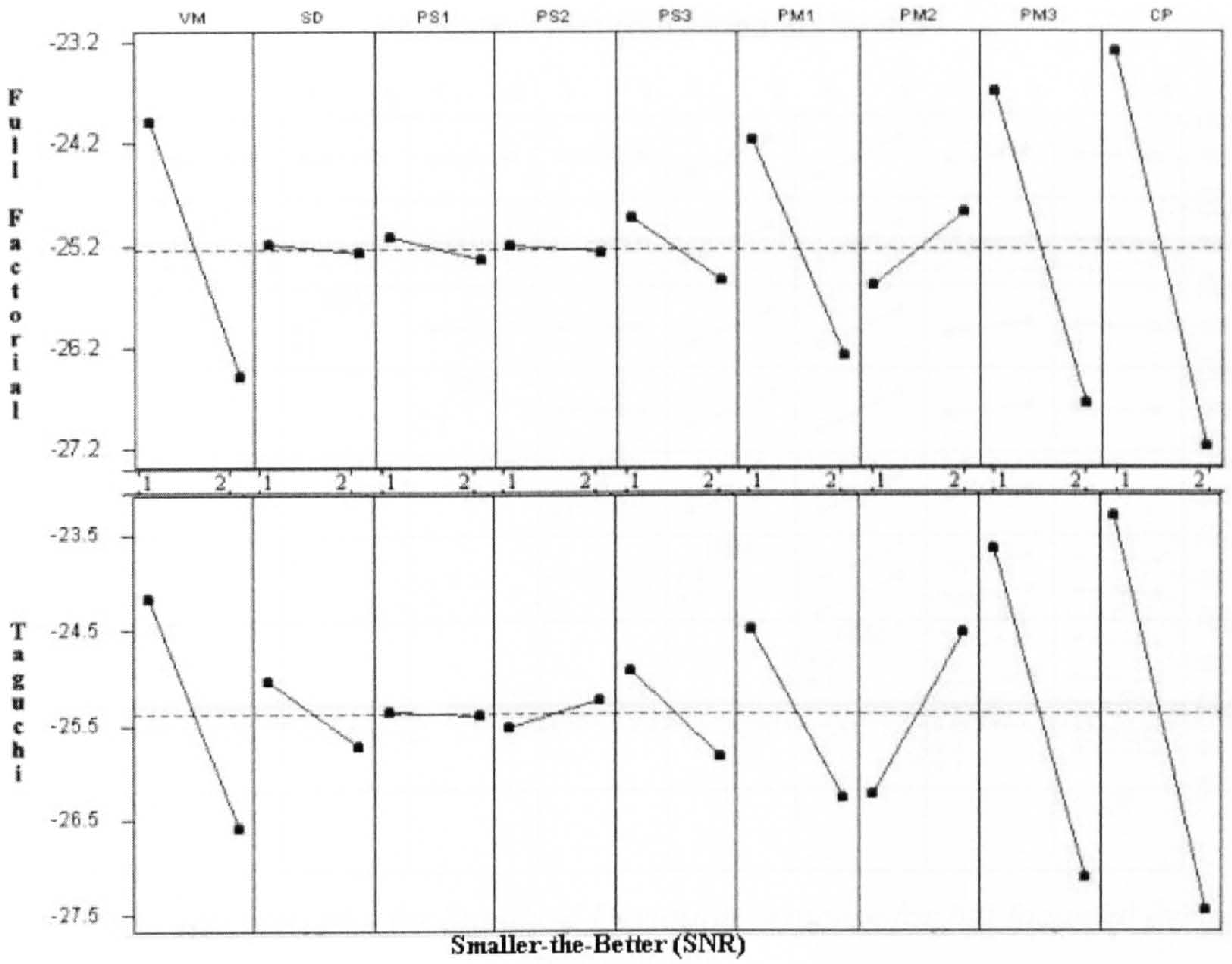


Fig. 4.6 Main effects plot for Smaller-the-Better (SNR) response (traffic flow).

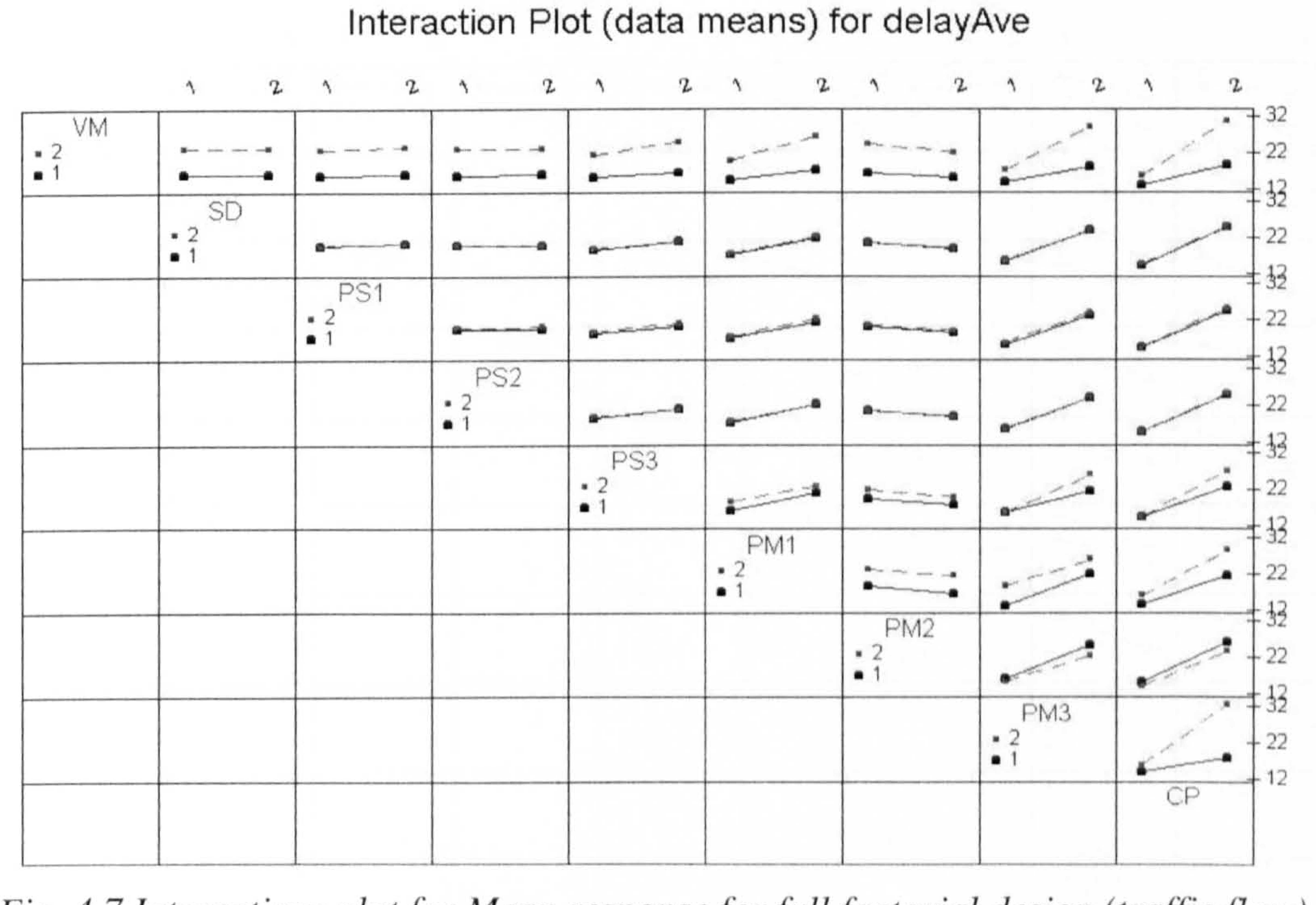


Fig. 4.7 Interactions plot for Mean response for full factorial design (traffic flow).

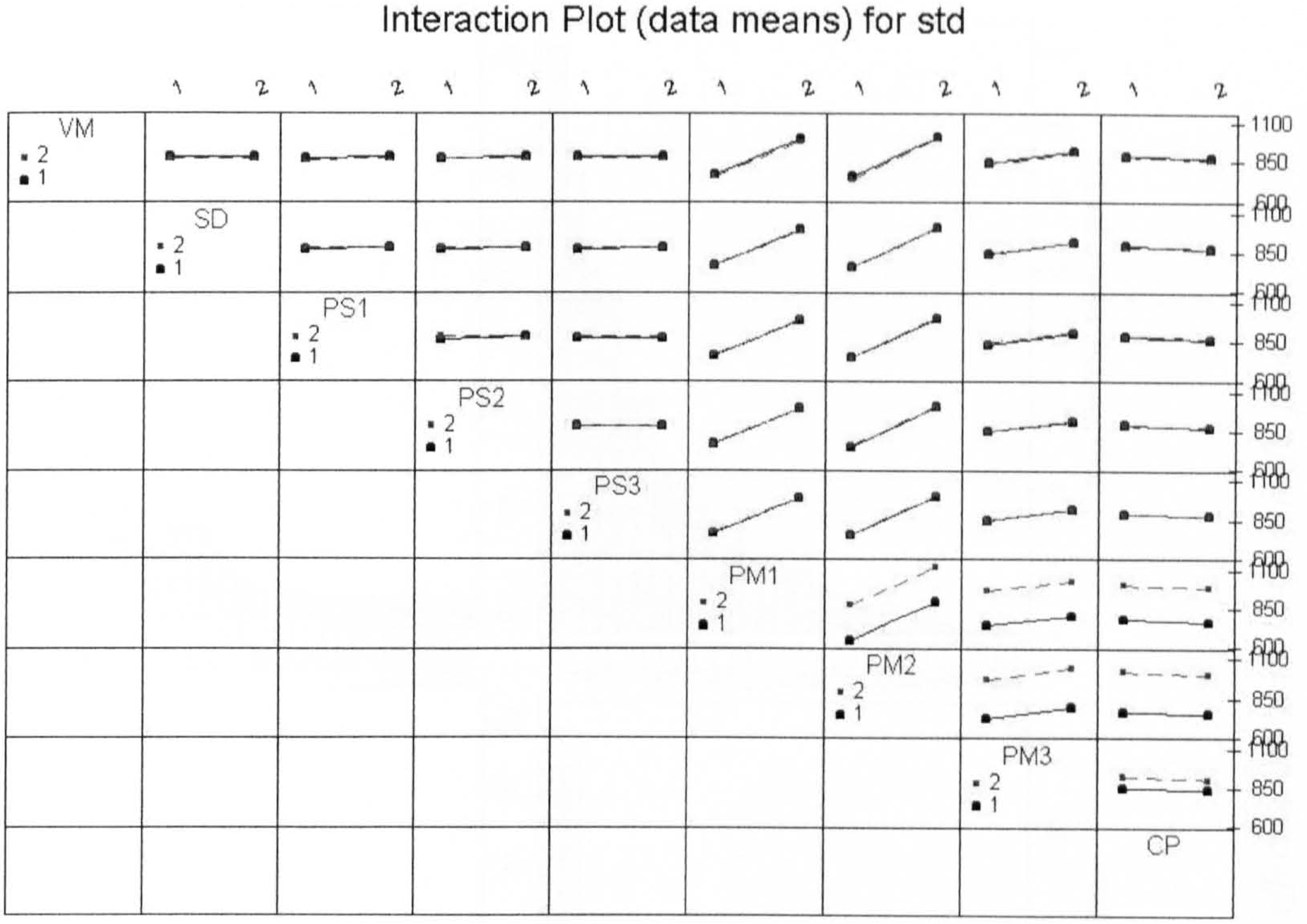


Fig. 4.8 Interactions plot for Standard Deviation response for full factorial design (traffic flow).

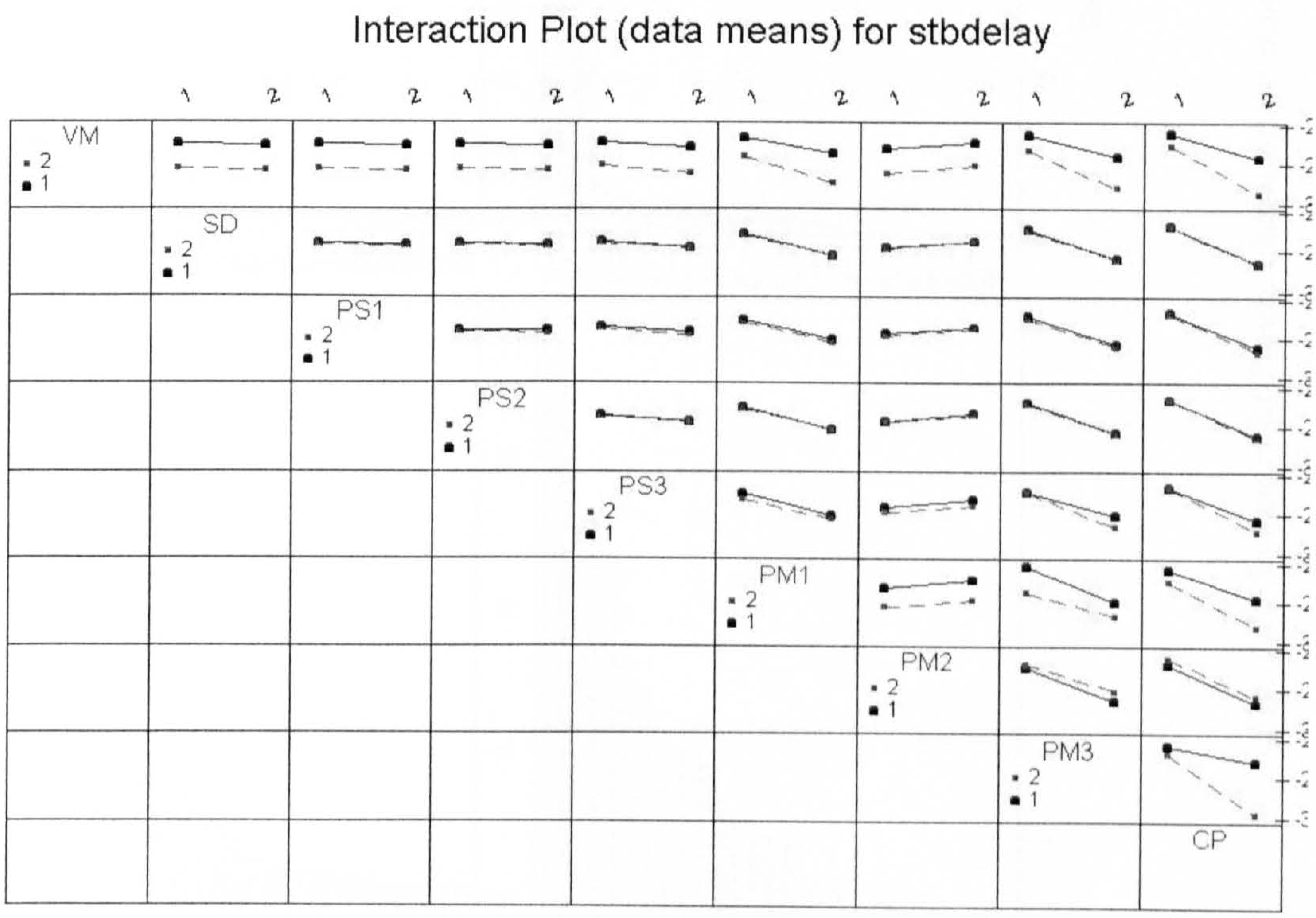


Fig. 4.9 Interactions plot for Signal-to-Noise ratio response for full factorial design (traffic flow).

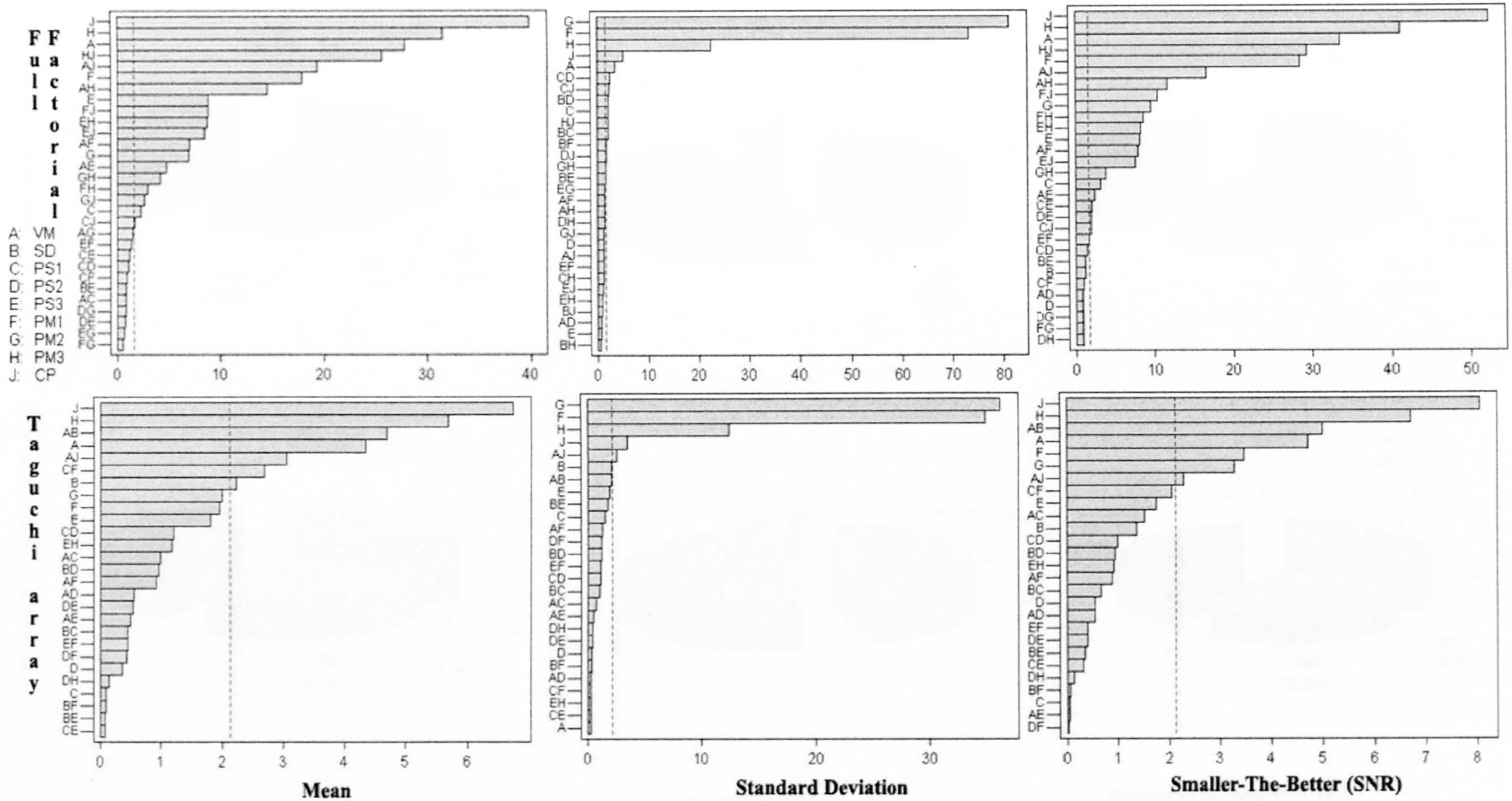


Fig. 4.10 Summary of Pareto charts of the standardised effects (Alpha=0.10) for traffic flow.

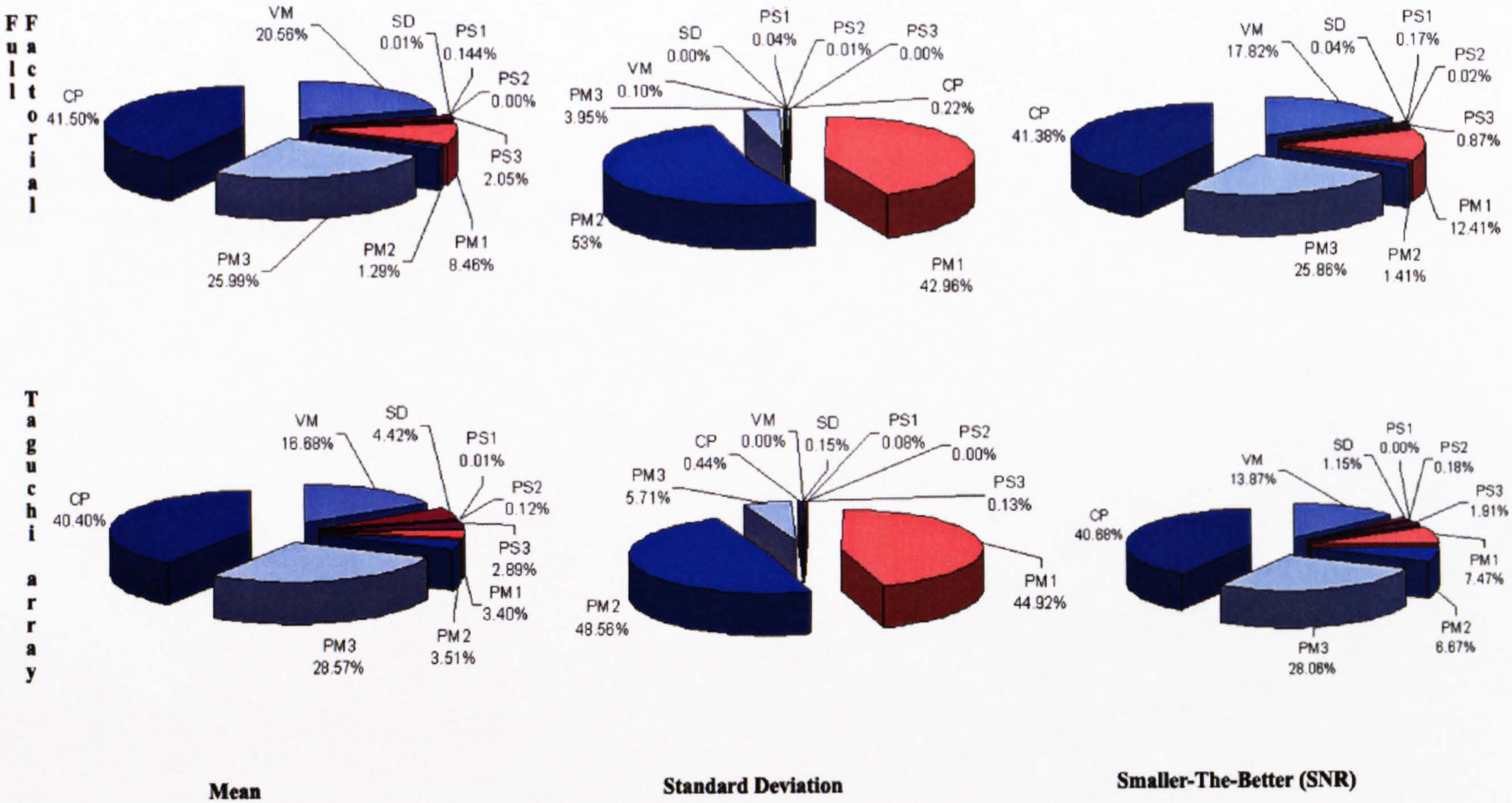


Fig. 4.11 Delay time percentage contribution of the effects (traffic flow).

4.4 Discussion

4.4.1 Statistical methods investigation

There is no doubt that one of the important findings in this case study is the fact that SNR is strongly correlated to mean and, therefore, to median. Taher and Anderson (1993a, 1993b) and Taher (1995) pointed out the occurrence of this type of correlation in some physical experiments, specifically in their metal cutting and brittle materials case studies. A similar situation was obtained for the metal cutting case study in this work, though other variables might have affected the outcome (Chapter 3). The significance of this finding is that usually the correlation of these metrics has occurred within physical experiments and not in different environments such as computer simulations. Certainly, the correlation issue (between mean and SNR) may have an effect on other aspects of the case study, but the actual implications of these were not explicitly studied in this work.

The most interesting result from an engineer's point of view is that estimation of effects using several tools (ANOVA, Pareto charts, Main effect and interaction dot-line plots, etc) on the three responses (mean, standard deviation and SNR) was very similar from both array types. Therefore, further analyses using data from this case study, like those performed later in this work (Chapter 6), are expected to suggest that Taguchi arrays can perform well in certain aspects such as determining related contribution and order of importance.

The nature of the experimental design in this work allows a deal of flexibility thanks to the conception and application of randomisation and blocking techniques into it. Blocking (based on controller type as the blocking factor) was done to automate simulation tasks during the experiment and not because there were factors really difficult to change, contradicting in some way the idea (suggested by findings on Pareto charts) of the experiment being affected by the presence of a Split-plot design. The idea of blocking influencing results in simulated experiments is very unlikely as opposed to physical experiments, which are affected by noise (environmental) factors.

Another important aspect is Taguchi's assumption of controlling dispersion independently of location. Pareto charts highlighted that the most influencing factor for location was not the one hinted for dispersion (and viceversa) which might hint that Taguchi's indication could be feasible in some situations. However, it may not be responsible to make such an assertion with the tools and strategies utilised so far. A proper evaluation may require further experimentation in which factors are adjusted to suit one response, optimise that response and then assess how the other response reacts. On the other hand, other important Taguchi assumptions, such as the unlikely presence of third-order interactions in experiments as well as the recommended confirmation runs, were not evaluated due to software limitations (the former) and resources availability (the latter).

Aspects investigated in this case study related to Taguchi methods have pointed at both positive and negative directions. On the positive side, factor significance prediction qualities of Taguchi arrays have been tested throughout this case study obtaining clear indications of a matching performance with full factorial arrays. This may indicate that, despite what has been suggested in the literature (Chapter 2) about some array construction deficiencies, they are still able to identify (at a trade off: inability to determine significance) aspects such as related contribution and order of importance. Also, Taguchi's suggestions of controlling dispersion effects independently of location effects were found feasible in this case study. However, these are not conclusive as other underlying aspects in the data analysis procedures may indicate otherwise under other circumstances.

4.4.2 Traffic flow investigation

There were some important findings in relation to the main factors. Profile magnitudes as a whole were found more important than their slope counterparts. This suggests that changes in vehicular flow may have a higher incidence in delay times than the way this flow changes. Furthermore, the fact of having one of the profile magnitudes outstandingly significant may suggest that controlling and/or estimating the vehicular flow into the intersection would be as influential as the use of different controller types. Though controller type was the most significant factor with nearly 50% of the location effects, the combination of the three profile magnitudes counted for nearly 100% of the dispersion effects. Also, the effect of profile magnitudes on location may be considered as negligible so their consideration, together with controller type, within a "unifying" model would be beneficial and robust. Notice that the incidence on dispersion of profile magnitudes is not evident for SNR response, which, together with those correlation issues, may be another proof of its inefficiencies as a metric. Going back to the most influential factors for location (controller type, vehicle mix and profile magnitude 3), results indicate that traffic responsive controller, low vehicle mix and a Sunday profile are best. At the same time, all profile magnitudes with Sunday profiles, fixed time controller and high vehicle mix are best for dispersion effects. This contrast of settings for both controller type and vehicle mix is very interesting because variation is not generally acknowledged as significant in transport engineering, which generally relies on the effects of location. These results suggest that there may be two practical general profiles for the network: a first one with a uniform travel time thanks to the reduced traffic (Sunday profile and low vehicle mix) with a controller changing depending on the load, and a second one with variable travel time (for which adjustment and optimisations should be considered) in which a fixed time controller may be required to rule the assorted traffic (high vehicle mix).

Application of Design of Experiments to traffic flow simulators is an interesting and promising research field. Determination and identification of significant effects/factors through either screening or factorial experiments have paid off in, at least, this case study. The fact that some theoretically important factors, such as speed distribution, were not found to have a significant effect on either location or dispersion makes it even more interesting. On the other hand, importance of vehicle mix, controller type and profile magnitudes, either combined or stand-alone, pointed at a suggested careful consideration and study of these variables at a later stage for a possible response optimisation investigation.

4.5 Recommendations

4.5.1 Statistical methods investigation

Split-plot designs, and their variations, have been pointed out by statisticians (Grove and Davis, 1992; Wu, 2000) as a fairly unexplored area, particularly when data comes from computer experiments. Data analyses in this case study suggested the unlikely possibility that a split-plot design type may be present in the data. Thus, a deeper investigation on that respect is suggested.

Despite being studied very briefly in the metal cutting case study (Chapter 3), it may be worth studying the evaluation and comparison among different varieties of linear graphs for a particular Taguchi array. It may provide more hints on the study of interactions, as well as being the starting point for the development of an approach aiming at their effective use in engineering environments.

4.5.2 Traffic flow investigation

Response choice may be the determinant for defining the approach to follow when studying traffic flow. Depending on the response, the use of Genetic Algorithms (Chapter 5) may be helpful with optimising the search for delay and travel times. Some applications can be found in the literature (eg Foy *et al*, 1992; Clement and Anderson, 1997; Sung *et al*, 1997) particularly for optimising limited traffic networks and signals using Genetic Algorithms and Neural Networks (either combined or stand alone). However, it has been demonstrated in this case study that some factors have a greater effect on delay time for these particular settings of the traffic flow simulator, which hints that "tweaking" these factors may enhance responses obtained in similar types of experiments. Therefore, an approach where optimised signals (through Genetic Algorithms) feedback the system as an initial condition (starting point), using this initial condition to carry out a designed experiment which would "tune" the previously identified significant factors and thus enhance the simulator performance, might be worth investigating.

Chapter 5

Genetic Algorithms Parameter Optimisation

5.1 Objectives

Since Genetic Algorithms (GA) were developed by Holland (1975) and colleagues, many authors (eg De Jong, 1975; Goldberg, 1989) have put great effort into the study, development and diffusion of these relatively novel optimisation techniques. Widespread applications in several fields reflect the simplicity and power of these algorithms, whose improvement (adaptation and survival) capabilities have proven to be theoretically and empirically robust for searching complex spaces (Goldberg, 1989). Recently, research on genetic algorithms has been focused on robustness, which is, in this case, the balance between efficiency and efficacy necessary for survival in many different environments (Goldberg, 1989). In this quest for robustness, development of simple and advanced genetic operators and selection methods have played an important role in recent years. Thus, either variations or new operators have been developed to suit specific needs for specific problems and implementations. The outcome of this development phase is a high number of operators which require some expertise from the user to define their ideal/effective settings.

In most investigations GA parameter settings are done empirically. Evidence of this can be found in the literature (Salomon, 1996a) and suggests that a more systematic and efficient approach may be useful. GAs with generic parameter settings can find worthwhile solutions in a reasonable amount of time but their performance can be improved by tuning their parameter settings

(Goldberg and Miller, 1995). Through this parameter tuning, efficiency may be gained from the application of Design of Experiments (DoE) to an investigation that would focus on the general use of Genetic Algorithms and address issues related to the appropriate choice of standard operators (eg appropriate population size and choices for crossover and mutation modes and probabilities) and whether choices for these interact with each other. Therefore, the main objective in this case study is to identify the best combination of settings for some of the principal genetic operators by using factorial experiments and statistical analysis to make the search more robust and effective. In order to fulfil these objectives a typical combinatorial engineering problem, the Out-Of-Balance-Force due to non-identical masses attached to a rotor, has been implemented into a GA. This is a type of problem which cannot easily be tackled by conventional optimisation methods and which is also known to stretch the capabilities of heuristic methods such as GAs, because there are few information links within it that point towards the optimal solution.

In addition to this, continuing with the framework proposed in this work (Chapter 1) for the study of Taguchi methods, the data generated in this case study would enable testing of the suitability of Taguchi methods for these types of simulation/problem, as well as a comparison with "traditional" DoE implementations.

5.2 Background to the case study

Many engineering design problems are very complex in nature as well as being discontinuous or discrete in structure and are therefore difficult to solve with conventional optimisation methods. In recent years, GAs have received considerable attention regarding their potential as a novel optimisation technique with an "easy" implementation that can be applied to a diversity of problems. There are many efficient optimisation methods and techniques, eg Evolutionary Operation (Box, 1957), Simplex Method (Spendley *et al*, 1962), Modified Simplex Method (Nelder and Mead, 1965), and heuristic methods such as Simulated Annealing (Laarhoven and Aarts, 1987: Press *et al*, 1992), Tabu Search (Glover, 1986) and GA (Holland, 1975), that can be used to solve this wide range of problems. Comparisons of those optimisation methods can be found in the literature (eg Luangpaiboon *et al*, 2000), where it is pointed out that GAs are attractive as tools for various optimisation tasks and appear to have the cutting edge in most engineering applications. There are several reasons to support this. Firstly, it is believed that GAs, as multi-point search procedures, can find better solutions in a shorter time than (classical) one-point search procedures (Goldberg, 1989) as well as easily handling multiobjective optimisations. Secondly, even when the function may be difficult and complex (ie discrete, discontinuous and constrained problems) GAs are not affected because they operate at the coding level (Goldberg, 1989). Because of this, GAs are simple to implement whenever a problem simulation is available and require very little prior knowledge of the problem to solve it, one of the most powerful aspects of GAs (Clarke and Davies, 1997).

GA problems can be classified into two main groups: combinatorial optimisation problems, and constrained optimisation problems (Carden, 1993; Dandy *et al*, 1993) (Fig. 5.1). For instance, recent engineering applications of GAs have been in areas such as electronics, structural optimisation, etc (Carden, 1993;

Dandy *et al*, 1993). They have been applied to difficult-to-solve optimisation problems inherent in industrial engineering, operations research and manufacturing systems design. Operations Research has made this range of possibilities wider, a situation that has created a boom in other areas such as manufacturing and transport engineering (Foy *et al*, 1992; Clement and Anderson, 1997; Sung *et al*, 1997) where the application of GAs has been a success. The prevailing use of computer models and experiments for simulating real phenomena generates examples in virtually all areas of science and engineering. Computer simulation models typically have large numbers of variables available for investigation. This is because the functions are complicated and all the factors that may affect the output are known and readily available for experimentation. A GA may not be as complicated as models simulating real phenomena but may still have a large number of operational parameters that, if seen from the parameter optimisation viewpoint, suggests a wide area virtually unexplored and available for investigation. In relation to these parameters, Goldberg (1989) studied some genetic operators reporting findings on their performance and made some suggestions regarding operator settings. Crossover, mutation and selection operators improve the general fitness of the population (Gray *et al*, 1996) and are the three main GA operators (Goldberg, 1989; Cao and Wu, 1997). The significance of crossover probability (P_c) and mutation probability (P_m) in controlling GA performance has long been acknowledged in GA research. Higher P_c values appear to bring quicker new solutions into the population, but solutions may be disrupted faster than selection can exploit them if these are set too high (Cao and Wu, 1997). Similarly, despite mutation being a secondary GA operation (some mutation may be required to prevent premature convergence of the GA) the choice of P_m is critical to GA performance as large values of P_m may transform the GA into a plain random search algorithm. Many researchers (Davis, 1989; Fogarty, 1989; Grefenstette, 1986; Srinivas and Patnaik, 1994) have focused their investigations on identifying optimal settings of P_m and P_c, but most of them have applied "one factor at a time" and/or empirical methodologies undermining their practicality (Zuo, 1997).

Testing of these three main operators started with De Jong (1975) who performed extensive experimentation on GAs including some empirical tests on basic GA parameters. De Jong carried out a series of parametric studies on five problems (function suites) to investigate variations of simple GAs, different genetic operators and their incidence on the performance. He found good GA performance for his test functions whenever high crossover probability (P_c=0.6), low mutation probability (inversely proportional to the population size and around 0.001) and a moderate population size were chosen. He also reported that when small population size (50 to 100 individuals) is combined with a number of generations between 10 and 20 there is a high probability of including optimal or near optimal individuals. Later on, Goldberg (1989) studied several parameter settings through some GA applications and agreed with the De Jong (1975) recommendations for population size, number of generations, crossover and mutation probabilities. In more recent developments, standard parameter settings have emerged (eg Bäck, 1993; Bäck and Schwefel, 1993; Goldberg, 1989; Mühlenbein and Schlierkamp-Voosen, 1993; Potter and De Jong, 1994) and it is generally agreed that a GA should use high crossover and small mutation probabilities (Salomon, 1996b). Zuo (1997) suggested mid-sized populations (50-200), high crossover probabilities (0.5-1.0) and low mutation probabilities (around 0.1%). Analogously, other authors (Keane, 1996; Dakev *et al*, 1997; Cao and Wu, 1997; Rogers and McCully, 1999) backed these suggestions with implementations considering recommended ranges for population size (50-100), crossover probability (0.7-0.95), mutation probability (0.005-0.1) and number of generations (10-500).

Studies have not been focused on finding the ideal parameter settings only but on finding also parameter significance as well as relationships among them, though pointing at specific problem types. The effectiveness of crossover has been illustrated and presented experimentally (eg De Jong, 1975). Schaffer and Eshelman (1991) empirically compared mutation and crossover concluding that crossover can exploit aspects mutation alone cannot. Apart from the empirical investigations, efforts have been directed toward theoretical comparisons between mutation and crossover (eg Spears, 1992) and between different crossover operators (eg De Jong and Spears, 1992). However, these theories are not enough to predict when and how much to use crossover, or what form of crossover to use under certain conditions (Spears, 1995). Moreover, these theories should not be considered as complete as they do not consider population size, which can affect the utility of crossover operators (eg De Jong and Spears, 1990), nor the effect it has on mutation. For instance, if population size is small mutation appears to be more useful than crossover whilst crossover appears to be more useful than mutation when population size is large (eg Spears and Anand, 1991). Other factors, such as the representation, selection scheme and fitness function, may all have an effect on the relative utility of crossover and mutation (Spears, 1995). Salomon (1995) demonstrated that any GA featuring broad mutation operators, an elitist selection scheme and a mutation probability equal to $1/n$ (being n the problem's dimensionality), necessarily converged with a $\theta(n \bullet ln(n))$ complexity if applied to some decomposable functions regardless of the selection mechanism (eg truncation, roulette wheel) or population size. He tested with eight particular functions including five De Jong test functions, so the findings only covered one particular type of problem (continuous/mathematical functions).

An alternative way of optimising GA parameters is targeting performance. Researching and focusing on aspects that take up more computational resources (time) may be an alternative way to achieve this. For example, Povinelli and Feng (1999) indicated that the computational effort spent on evaluating the fitness function may far exceed that of the genetic operators because evolving populations tend to diminish diversity so the same chromosomes are frequently re-evaluated. Therefore, they demonstrated through several examples an approach where storing fitness values (from the most recently evaluated chromosomes) in a hash table would dramatically improve GA performance, which obviously gives more benefits as the evaluation function gets more complex.

Due to the complexity of the problems GAs have been applied to, more sophisticated and specialised operators are required increasing the number of operator parameters to optimise. In more realistic simulation/problem GA environments, because of the high number of parameters involved, "tweaking" them to influence the response may be an endless process. Improvements in areas such as selection, scaling and ranking methods and, additionally, more advanced operators (inversion, dominance, mating restriction, niche, etc) have come forward (Table 5.1). This increases further the number of GA operating parameters to work on. Generally, some of the principal genetic operators, such as crossover, mutation mechanisms and probabilities, have been set/determined empirically, which may not be beneficial under certain conditions. The variety of GA software available usually requires various parameters to be set or choices between versions of GAs to be made by the user. Guidance on these choices tends to be scarce in the literature and, if found, either focuses on specific problems/classes of problems or is based on "one factor at a time" tests. Apart from being inefficient, "one factor at a time" tests are known for their inability to detect interactions. Extensive experiments (eg Cliff *et al*, 1992; Floreano and Mondada, 1996; Huber *et al*, 1996; Nolfi and Parisi, 1995) on robotics applications have shown that GAs may perform poorly due to significant parameter interactions. This evidence justifies an approach in which the use of factorial experiments and statistical analysis (such as ANOVA) could contribute to the optimisation of GA parameters.

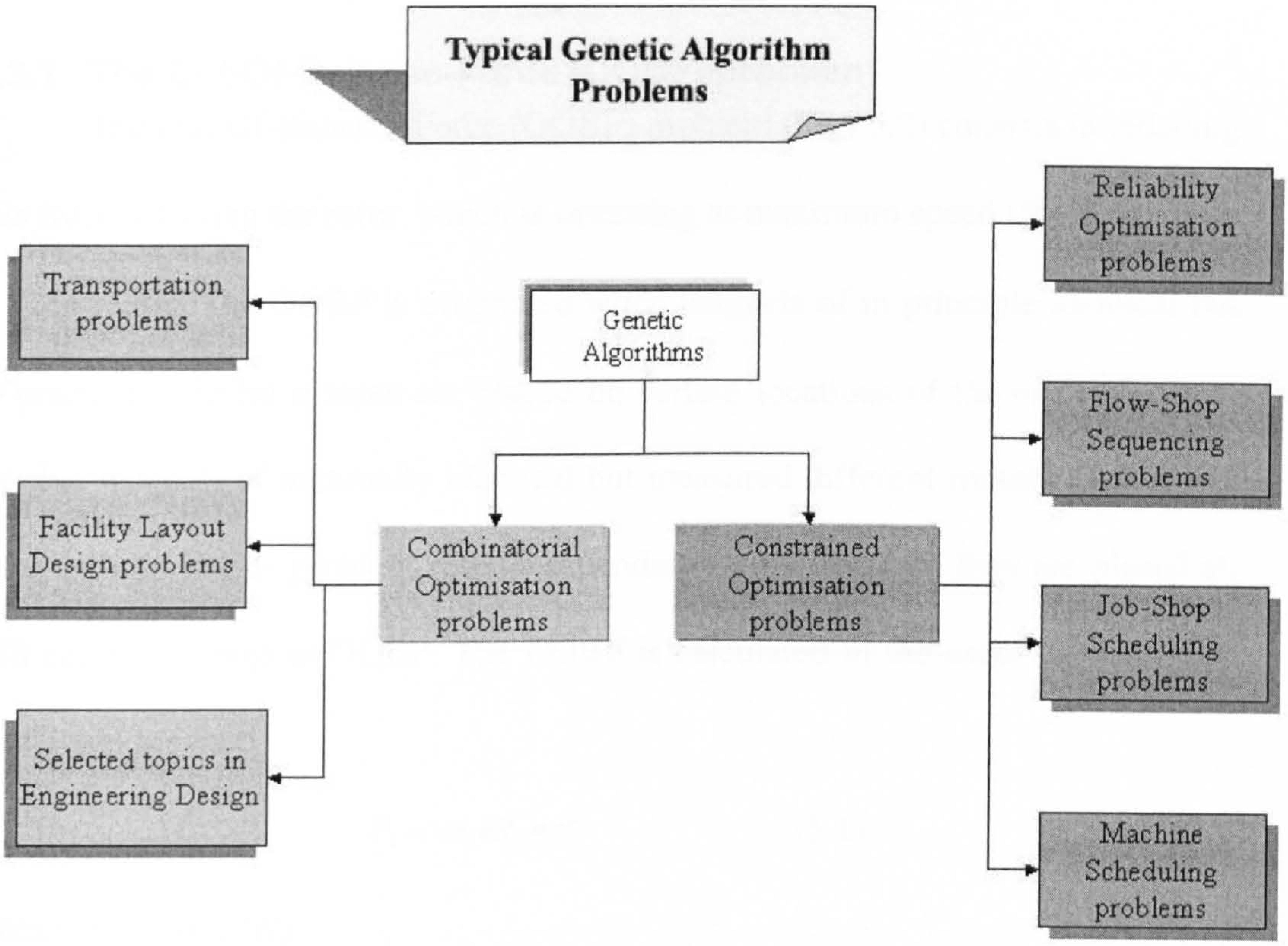


Fig. 5.1 GA problem types classification (Gen and Cheng, 1997)

Advanced Operators		
Low Level	**High Level**	**Population oriented**
Dominance and Diploidy	Niche exploitation	Migration
Inversion		
Intrachromosomal duplication	Speciation	Mating restriction
Deletion		
Translocation	Sexual differentiation	Sharing functions
Segregation		

Table 5.1 Summary of some GA advanced operators (Davis, 1985; Smith, 1985; Goldberg and Lingle, 1985; Goldberg, 1989).

5.3 GA parameter optimisation case study

5.3.1 The Out-Of-Balance-Force (OOBF) problem

The Out-Of-Balance-Force (OOBF) problem (Fig. 5.2) consists in reducing this force affecting the rotor, which is operating at maximum speed (50000 rev/min ≈ 5236 rad/s). The OOBF is originated when magnets of in principle identical but in practice different masses are placed on certain locations of the circumference. Twelve magnets of nominally identical but measured different masses (Table 5.2) were utilised in this problem, which depending on the location they are placed at, will cause a change in OOBF. The OOBF is calculated in the usual way for each individual magnet:

$$F_i = m_i \bullet R_g \bullet \omega^2 \qquad (5.1)$$

where: F_i = *force (N)*

m_i = *individual magnet mass (kg)*

R_g = *distance to centroid (m)*

ω = *rotational speed of rotor (rad/s)*

A proper evaluation of this problem should also consider variations in forces induced by assembly changes in the distance to centroid R_g and also of the angular location of these. The idea of studying this problem in the present case study is to tackle the parameter optimisation through it, so it should be kept simpler and it is assumed that R_g and the angular spacing ($\pi/6$) can be effectively constant. Also, because of the nature of the problem (pure combinatorial type) unless some assumptions are made it is still among the most difficult types to solve (Gen and Cheng, 1997). Thus, considering those assumptions and knowing m_i, R_g

is required to calculate F_i (Equation 5.1). The force components can be calculated by decomposing R_g into both dimension components, $(R_g)_x$ and $(R_g)_y$, for each individual magnet. Thus:

$$(F_x/\omega^2) = \sum (m_i \cdot (R_g)_{x_i}) \qquad (5.2)$$

$$(F_y/\omega^2) = \sum (m_i \cdot (R_g)_{y_i}) \qquad (5.3)$$

Then, resolving the force components:

$$(F/\omega^2) = \sqrt{(F_x/\omega^2)^2 + (F_y/\omega^2)^2} \qquad (5.4)$$

Each magnet configuration represents a solution, given by the arrangement of the magnets in 12 different orders for a total of 4.8E8 possible combinations/permutations (12!). This number of combinations is not so high that in this case a systematic search procedure allowed the true optimal solution (the arrangement of magnet masses leading to minimum out of balance force) (Section 5.4.2) to be found. This is therefore a benchmark against which the effectiveness of different GA implementations or parameter settings may be judged. It is not expected to always reach the optimal solution, but a near optimal solution with low OOBF.

Magnet	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Mass (g)	25.85	25.66	25.89	25.94	25.98	25.95	25.97	25.82	25.90	25.75	25.56	25.74

Table 5.2 Magnet masses for the OOBF

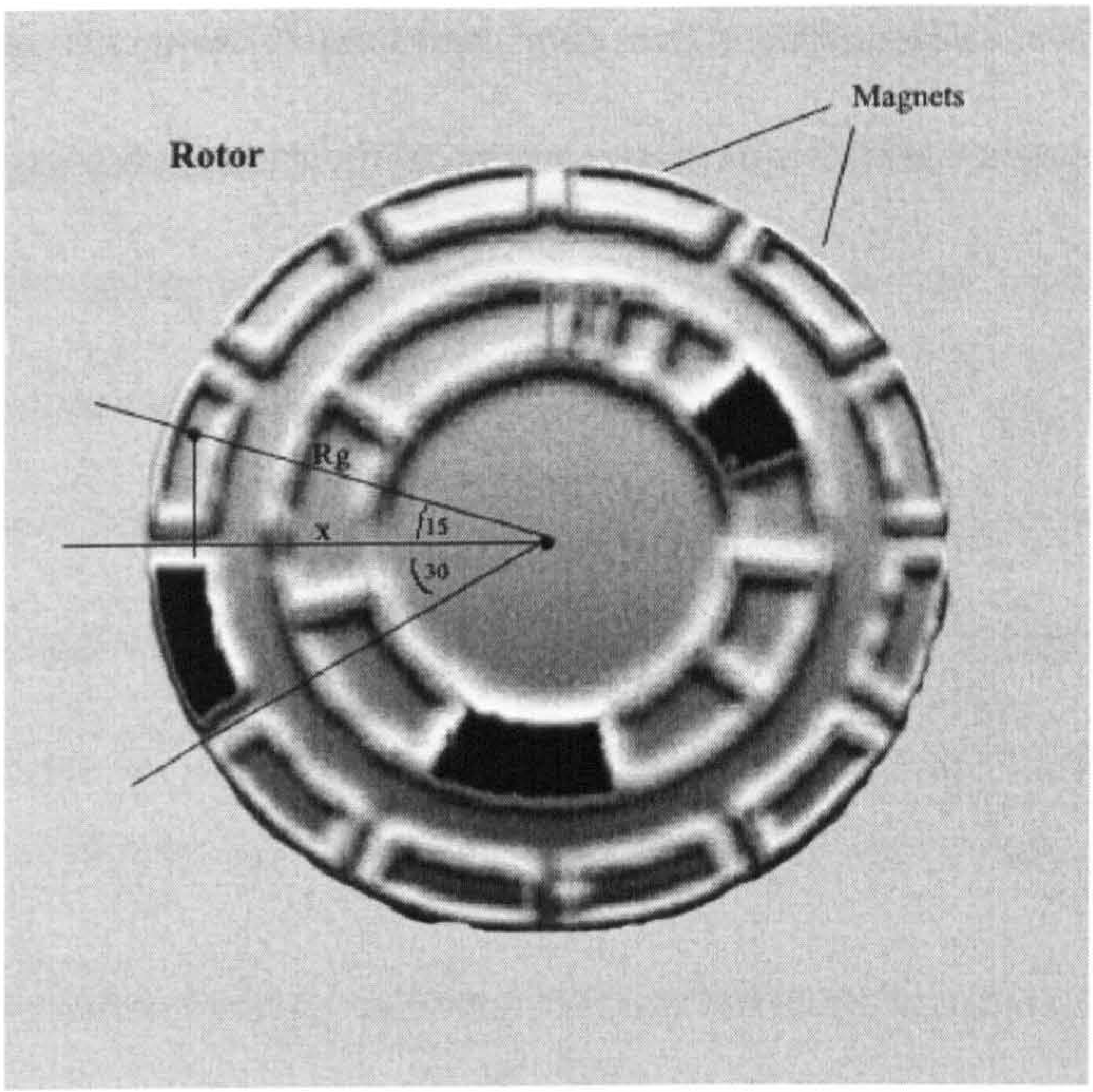


Fig. 5.2 Rotor Scheme

5.3.2 GA implementation

GENALG (Anderson and Simpson, 1996) was the GA software utilised for this problem because the source code was available for modification and it allowed easy variation of a number of operational parameters. Obviously some of GENALG subroutines need to be changed in order to accommodate the OOBF problem. Most of the changes, involving reproduction operators and generation of new genes, were done to prevent gene duplication (duplicates reduce population diversity and requires redundant simulations) as well as guaranteeing that each magnet (gene) has been placed in only one location. GENALG has a built-in module for duplicate removal (Anderson and Simpson, 1996). This also involved modifications to the random generation of new individuals, which relies heavily on random number generation. The subtractive method of Knuth (Press *et al, 1992*) was used to generate the sequence of random numbers as there is no correlation in successive terms.

Encoding the OOBF problem was not complicated. Making use of the generated random numbers, twelve genes (each one representing a magnet) were obtained until the string (chromosome) was completed with no gene duplication. Each string represents a magnet combination and therefore an OOBF evaluated through the fitness function (equations 5.1 to 5.4). Fitness value is the mean of the total OOBF applied on the rotor and is scaled to allow strings to be weighted for ranking and further selection. The fitness function used has the following inverse form:

$$Fitness = \frac{1}{F \cdot 10^3} \qquad (5.5)$$

Notice the scaling factor (10^3) added in equation (5.5). Fitness scaling is generally important for relieving selective pressure and tackling premature convergence (Goldberg, 1989), though linear scaling like this should not have any effect. The inverse form of the fitness value allows obtaining better fitness if lower OOBF (desired condition) is achieved from the chromosome evaluation, and vice versa.

5.3.3 Experimental design phase

GAs being supposed to be an efficient optimisation technique may lead to the conclusion that they are sufficiently robust and "optimised" so that little or no further work is needed to fine-tune their performance. Much research is done on new variants, generally, to make this evolution process more capable and to match the natural one, and has been focused on addressing particular solutions, with the developments extended to apply to a wider spectrum of problems thereafter. Development of these methods (operators) may be unlimited as there will always be the need to address new issues with new problems. However, the issue is not only the choices of operators but also determination of their ideal (initial) settings which may enhance the search for an optimal solution. This clearly points at the direction in which the definition of the current research should aim: how to optimise the parameter selection (and setting) process? An effective way of dealing with the high number of parameters (and their settings) is the application of DoE techniques. Therefore, the problem to tackle in this case study is the application of DoE techniques for the parameter optimisation stage to enhance response(s) performance. Also, this approach focuses on using DoE to reduce the time spent on "tweaking" system parameters to obtain the preferred response(s), as well as to enhance and/or optimise the response(s).

The next step, "brainstorming" for factors and levels, followed the process outlined in Chapter 3, with the additional constraint that it was desirable to avoid repeating other GA studies being conducted within the Department (eg Pongcharoen *et al,* 2000). Despite this the outcome was very rich in options, so the range of operators that can be selected has to be narrowed. For this reason, only simple GA operators were considered, leaving more advanced operators (Table 5.1) for further study elsewhere. Initially, a group of the most common operators (and some suggested settings) was compiled during the "brainstorming" (Table 5.3). These operators involved at least the three essential operations of "conventional" GAs, selection, crossover and mutation (Goldberg, 1989), together with other essential parameters related to population and generation sizes.

Parameter optimisation was evaluated through the OOBF problem. Response choices may vary depending on the focus of the GA application under study. Any of the performance (eg diversity, maximum, minimum, mean and standard deviation of fitness) and execution (eg convergence rate and convergence threshold) indicators may easily be a candidate for a response in this case study. Maximum fitness, also called Peak Value, is a common choice for response as most GA implementations are aimed at optimisation tasks. Naturally, Peak Value should be among the selected responses because the problem studied here sought to find the minimum OOBF (maximum fitness). Peak Value is the maximum fitness reported for all seeds on each GA run. Studying Peak Value certainly is very desirable as the idea is to be as close as possible to the optimum. Mean, standard deviation and SNR of fitness were also considered and selected, as they are required for the comparison of experimental designs, which is also studied here. Additionally, mean fitness of a population is a good performance indicator for the overall search, as higher means would be a sign of the absence of less desirable low fitness individuals. Standard deviation, on the other hand, may be seen as a measure of population diversity, seen as essential to avoid premature convergence or convergence to a local and not global maximum. Regarding SNR, Larger-the-Better (LTB) should be appropriate for this type of problem where fitness is to be maximised.

Convergence rate and convergence threshold were the other two possible responses to be selected. The former is defined by (Goldberg, 1989):

$$CR = \frac{(CG)*100}{MAXGEN} \tag{5.6}$$

where *CR* is Convergence Rate, *CG* is Convergence Generation (Generation in which GA first converged) and MAXGEN is Maximum number of generations. The latter is an interesting termination method/operator suggested by Rogers and McCulley (1999), where a converged population is one for which the average fitness is at least a determined percentage of the best fitness (with the best fitness seen so far). Despite both being interesting options to study, they were not selected as responses for this case study. The data required for calculating convergence rate was included within the information obtained from GENALG at each run. However, the amount of data obtained for this response is equal to the amount obtained for this whole case study, which would require a separate case study for careful evaluation and can be the object of further investigation (Section 5.6). Convergence threshold was not selected as a response because of its "threshold percentage" which may work as a parameter instead if varied. Implementation of this operator required extra coding into GENALG that, although it is not a similar issue as with convergence rate, may have a certain effect on the GA performance (turning it into a factor depending on its application).

Limiting the brainstorming process to the list of common and simple operators (Table 5.3) was the first step for reduction of the number of factors to be studied, though it was not enough so further reductions were required. Goldberg's (1989) "basic" elements were the start for the factor reduction stage. Mutation, crossover and selection were basic factors to be considered in any experiment. These three have at least two options to choose: the method and the internal settings (ie probability), increasing substantially the number of factors. The reduced list of factors would consider:

- **Selection:** There are many selection schemes for GAs, each with different characteristics, among which tournament selection has increasingly being used for different problem domains (Goldberg and Miller, 1995). It has the ideal qualities for a selection mechanism: simple to code, easy to implement and has an adjustable selection pressure (Goldberg and Miller, 1995), which enables a GA to identify optimal or near-optimal solutions (Goldberg *et al*, 1993). Tournament selection has two parameters to choose, tournament size and number of winners, which were paired as levels into a fixed combination between size and number of winners (Table 5.4).

- **Crossover:** Although authors have recommended ranges for crossover probability (Section 5.2), there are also a wide variety of crossover types available, which still leave doubts on the ideal combination/selection of crossover type and its settings. Either of crossover probability or types are interesting factors to study as several problems differ on their recommended settings. In this case only a simple crossover type (two-points) was chosen, leaving as a factor crossover probability (P_c) to be varied. Too low or too high crossover rate are not good for a GA as they may affect the way exploration is done (Zuo, 1997). Therefore, P_c was set at two levels, low and high (Table 5.4), in order to determine which one of the extremes is better and how far can they go.
- **Mutation:** the criterion for selecting mutation types is analogous to that used for crossover. Mutation type and probability are the two simple options to consider. Mutation type was fixed at using single mutation (swapping two random genes) leaving mutation probability (P_m) to be varied at two levels. P_m was set at 0.1% and 1%. Intentionally the smaller value was picked at a level above zero. Zero probability would rule out mutation altogether which is not desirable as this study is not focusing on whether to use mutation (the benefits of using mutation have been reported in the literature, eg Section 5.2).

- **Population size:** The way the population is handled is deemed important as it may have an overall effect on the selection and reproduction mechanisms (which is done through defining population types and sizes) as well as affecting performance and efficiency. Regarding size, small populations are generally not recommended for providing insufficient sample size, but large populations, though they may prevent premature convergence, may also slow down the rate of convergence and require more evaluations per generation (Zuo, 1997). A simple GA may make use of a fixed population size. Thus, in this case study fixed population was used with population size as a two-level factor (100 and 1000). The low setting chosen is at the maximum size suggested by many authors (Section 5.2), but the intention is to go beyond that suggested boundary in order to see "how much is too much" (the point when too large population sizes affect GA performance).
- **Number of generations (iterations):** Though this is a termination parameter, and more effective ways to terminate the simulation may be available, its direct effect on resource (time) consumption remains a significant aspect. Criteria for its initial determination are mostly based on "rule of thumb", so its optimisation would be ideal for saving time to the optimiser as well as fighting premature convergence issues. This factor was set at two levels: low and high. These levels were set above the range suggested by De Jong (1975) but within the range recommended in the literature (Section 5.2) (Table 5.4).

Remaining factors mentioned at the brainstorming stage (Table 5.3) were fixed at single values. Inversion was ruled out, as single mutation was preferred instead. At the same time, duplicates were removed out though with the actual software implementation there is no guarantee that some duplicates may not be removed under certain conditions (the replacement chromosomes are not tested).

Reducing the number of factors to study is a good way to reduce the number of degrees of freedom required in a design. This would widen the options for selecting a fractional (ie Taguchi) experimental design capable of coping with interactions with minimal amount of confounding. Thus, as in the previous case studies, the reference design used in this case study was the full factorial. Also, a Taguchi array (L_{16}) composed of data extracted from the full factorial design was chosen to test its ability to cope with these types of problem. The reduced number of factors made the full factorial design a viable option because of the few runs (32) required.

Those five factors (Table 5.4) gave final shape to the experimental arrays. The 2-level full factorial array is now 2^5, which is equivalent to 32 runs. No blocking techniques were applied this time, as none of the factors was difficult to set. Runs were performed in a fully randomised order. The Taguchi array, an L_{16}, should be composed of runs, with identical set up to those in the full factorial, extracted from the full factorial array (Section 3.4). The setup for the Taguchi array was determined through the use of linear graphs. There are six different possible combinations/arrangements of linear graphs available for this type of design, with the maximum number of main factors that can be studied without confounding ranging from 5 to 10. The particular linear graph selected for this Taguchi array (Fig. 5.3) distributes the 15 degrees of freedom available for estimation in this Taguchi design "uniformly" so it might be possible to estimate main and second-order interaction effects with minimal confounding. The linear graph utilised in this case study (Fig. 5.3) allows a maximum of 5 main factors that can be allocated in the Taguchi array, leaving the remaining columns (ten) available for error or interaction terms. Notice that the arrangement of the linear graph selected considers second-order interactions among all factors as in a full factorial design.

Factors		**Levels**		
Population	Type	Fixed	Variable	
	Size	Low	Intermediate	High
Chromosome length		6	12	18
Removal of duplicates		No	Yes (With mutation)	Yes (With new)
Number of generations		Low (Fairly often)	Intermediate	Higher (Less often)
Replacement	Fitness	Zero (never)	X value	High value
	Probability	Low	Intermediate	High
	Method	Mutation	New	
Tournament selection	Number of competitors	2	5	
	Number of winners	1	2	
Crossover	Probability	Low	High	
	Number of points	Single	Uniform	
Mutation	Type	Single (Swap 2)	Inversion (Swap 12)	Truncation
	Probability	Zero (never)	Small	
Inversion probability		Zero (never)	Small	
Age of muting pool		2	More	

Table 5.3 Summary of some simple GA operators (Davis, 1985; Smith, 1985; Goldberg and Lingle, 1985; Goldberg, 1989; Luh and Wu, 1999).

Label	Factor	Level 1	Level 2
POPSIZE	Population Size	100	1000
MAXGEN	Number of generations	25	99
XOVER	Crossover probability	0.25	0.90
MUTPRO	Mutation probability	0.01	0.001
TOURN	Tournament size/winners	5/2	2/1

Table 5.4 Summary of factors and levels for the GA parameter optimisation case study.

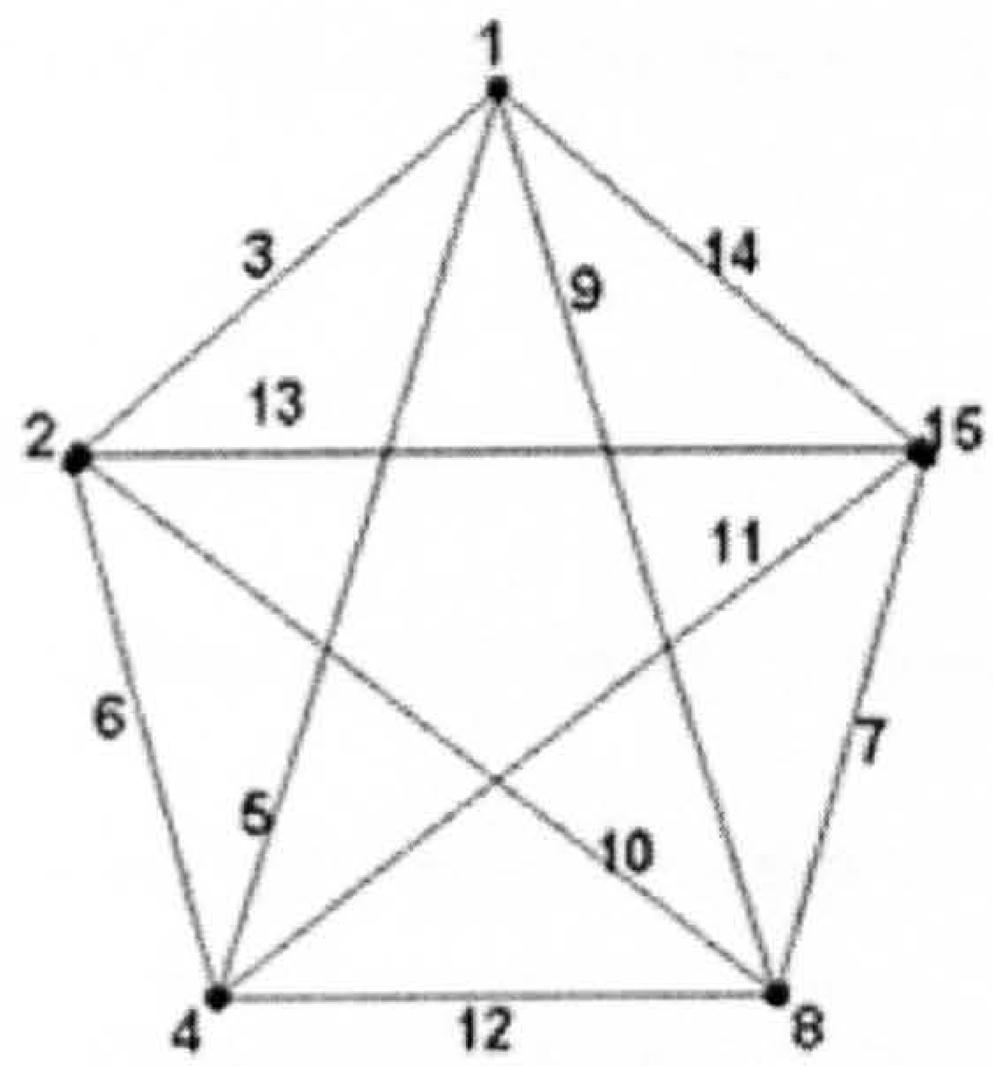


Fig. 5.3 Linear Graph selection for the L_{16} array (from Taguchi, 1987).

5.3.4 Data Acquisition phase

The experiment started with the preliminary task of setting up parameters in the GA implementation. The starting point in a GA simulation is the creation of a new population. Therefore, setting up parameters should start with producing a list of random numbers (seeds) which are used to randomly create the initial population. Sacks *et al* (1989) pointed out that lack of variation in computer experiments is due to the fact that every single run is identical, suggesting the variation of initial populations (eg seeds) to avoid floating point operations remaining the same and predicting exactly the same result with no variation. Based on this, eight random seeds were generated (0.0251, 0.152, 0.253, 0.41749, 0.54, 0.756, 08757, 0.958), using each one of them to produce the eight replications at every run throughout the full set of runs. Parameters (factor/level settings) were set appropriately according with the settings given by the experimental design. Then, the full set of runs with a single seed was generated through a batch job to automate the simulation process until the 32 runs were completed. The batch job will then resume with the same settings but starting with a different seed, repeating the procedure with the remaining seeds. Simulation output provides statistics for each generation (max/min, average, median and standard deviation of fitness) as well as information related to the best chromosomes of that and all previous generations.

At this point it should be noted that the same OOBF and hence fitness would be obtained for any particular sequence of genes, irrespective of which one was the "first" in the list, eg the two chromosomes in Fig. 5.4. Thus for any given sequence, there will be twelve chromosomes (one for each of twelve possible starting genes) giving identical OOBF and hence fitness. To investigate the possible impact of this a special method/operator, called RotChr (Rotating Chromosome), for modifying chromosomes to allocate specific genes in specific locations, was implemented. The method is similar to the Shift Operation Mutation type (Murata and Ishibuchi, 1994). In Shift Operation Mutation (SOM) two gene positions are chosen randomly, then the second chosen gene is inserted at the position of the first chosen gene with the remaining genes shifted to the right (Fig. 5.4). In RotChr a predefined gene is searched for throughout the string. Once this gene is located, the string is split into two portions: one from the identified gene (inclusive) to the right and another one to the left. Then, both portions are swapped maintaining their original gene order (Fig. 5.4). RotChr may be seen as an additional mutation operator, but its location within the GA dataflow may indicate otherwise. This method was implemented at the beginning of the simulation between the creation of new chromosomes and fitness evaluation, before the selection and reproduction mechanisms take place. RotChr does not interfere with mutation nor crossover operators as they are still carried out normally in the GA. Through the use of RotChr it would be possible to generate twelve new data sets (one data set per starting gene).

The reason for developing and inserting this method into the experiment was to explore whether the existence of different chromosomes with identical fitness would affect GA performance or whether the search could be refined through gene localisation. In this case study, data was generated for all twelve genes as the first gene. Therefore, two data sets were generated: one with the normal GA simulation (single set of 32 runs and 8 replications) and another one where RotChr was applied (Twelve sets of 32 runs and 8 replications each). Both data sets had exactly the same design settings as described previously.

Once the 256 runs (8 times 32) were completed for each of the two data sets (Appendix D1), the output containing the best fitness (and its respective chromosome) of each simulation was processed to give statistics such as mean, standard deviation, SN ratios and peak value. Mean, standard deviation and SN ratios were calculated from fitness obtained from all (eight) replications of each run. Peak value was the maximum fitness from all eight replications of the same run. Data organisation for the Taguchi array (Appendix D2) consisted in searching throughout the full factorial array for equivalent runs, defined in the Taguchi array with identical set up (excluding interaction columns), extracting from the full factorial array the whole row including parameters and data.

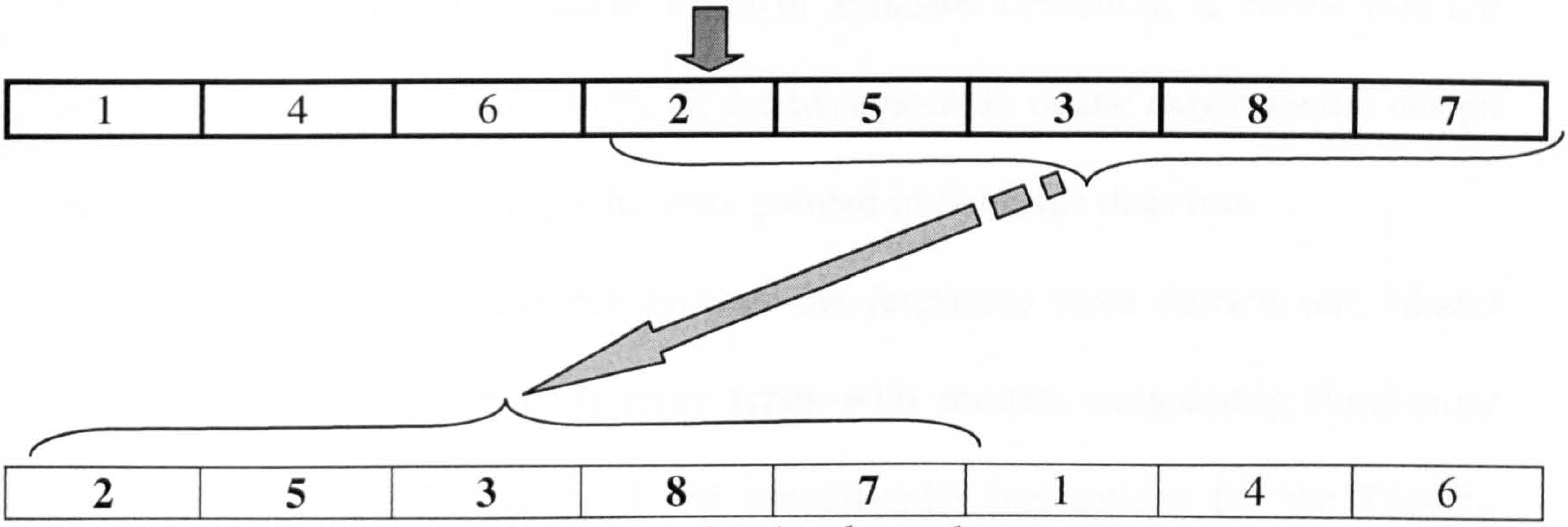


Fig. 5.4 RotChr method representation (each number represents a magnet mass from Table 5.2).

5.3.5 Data analysis phase

Analyses were carried out on the full factorial design in the first instance using the "normal" data set (RotChr method off) focusing on determining factor significance and optimal factor/level settings to maximise fitness. Then, similar analyses based on the Taguchi design for the same data set followed, with the addition of studying other inter-relationships/features for both full factorial and Taguchi arrays. This procedure was repeated for the other data set (RotChr method on) (results included in Appendix D3).

Values for mean, standard deviation, SNR and Peak Value were calculated run by run based on the fitness values obtained on each run of each array and considering the eight replications. Once these values were estimated, the analysis started with correlation tests to determine possible linear dependencies and/or relationships among responses (Table 5.5). Results suggested a direct correlation between mean and standard deviation, which explains subsequent relationships with other responses. Peak Value was also directly correlated to mean and therefore to standard deviation, though a stronger relationship with standard deviation was found. Links with SNR were weak as Larger-the Better (LTB) seems less strongly correlated to either mean or standard deviation. It seems that the presence of these correlations can be found regardless of the experimental design utilised, as results for the Taguchi array pointed in the same direction.

Next, ANOVA tests for each of the responses were carried out. Model suitability was tested on both array types with models considering third-order interactions for the full factorial and second-order interactions for the Taguchi array (Table 5.6). Due to partial confounding, the model for the Taguchi array was invalid for 2-way interactions (which forced consideration of a model with main factors only) and valid for main effects on only half of the responses (mean and LTB) (Table 5.6). These models confirmed the suitability of the full factorial for all main effects and 2-way interactions on all responses (Table 5.6), but only one response (LTB) made the grade for 3-way interactions (Table 5.6).

A summary table for the ANOVA test results (Table 5.7) was put together for both arrays and the four responses. Three main factors (population size, number of generations and mutation probability) were found extremely significant for mean, standard deviation and peak responses in the full factorial array. For the SNR response results were slightly different, as LTB identified all but mutation probability significant. Six second-order interactions (population size and number of generations, population size and crossover probability, number of generations and crossover probability, number of generations and mutation probability, crossover probability and mutation probability, tournament selection and mutation probability) were found significant for mean, in which three of them (population size and crossover probability, crossover probability and mutation probability, tournament selection and mutation probability) were also found significant for standard deviation and peak value. Again for SNR the situation was different to some extent with four second-order interactions for the LTB response (population size and crossover probability, number of generations and tournament selection, crossover probability and mutation probability, tournament selection and mutation probability). Most interactions involved significant main factors with the exception of crossover probability, which was present despite being found not significant on its own. Like the other case studies (Section 3.4), third-order interaction effects were also found here, though results were not uniform for this type of effect. Only one third-order interaction (population size, tournament selection and mutation probability) was found significant for mean response, in contrast with standard deviation and peak value which had two significant ones (population size, tournament selection and mutation probability; number of generations, tournament selection and mutation probability). SNR showed only one significant third-order interaction for LTB (population size, crossover probability and tournament selection). As can be seen, most of these interactions involved at least one of the two most significant factors (population size and number of generations) with the remaining main factors. ANOVA results for the Taguchi array were affected by partial confounding in the analysis, which can be seen in these results. For instance, no significant factors were identified for standard deviation and peak value responses. Only mean (population size and number of generations) and LTB (population size, number of generations and tournament selection) had significant main factor effects.

Determination of the best combination of factors and levels was done through the evaluation of dot-line plots for the full factorial array (Fig. 5.5). Best design settings were nearly identical (only with the exception of crossover probability) for mean, standard deviation and peak value for all significant factors identified in ANOVA. These settings suggested a population size of 1000, 99 generations, a small mutation probability (0.001), lower rate of selection (size of 5 and 2 winners), and any crossover probability as it seems not to affect the outcome. LTB was really off the mark as suggesting only a best setting for population size (larger) with other plots deemed non-significant. Visual evidence indicated similar results from Taguchi arrays (Fig. 5.6). Setting recommendations are analogous to those in the full factorial, with the exception of crossover probability and tournament selection which were found (for all responses) to have no effect on the responses whatever the setting was.

Other helpful plots, such as Pareto charts (Fig. 5.7 and 5.8) and interaction dot-line plots (Fig. 5.9 to 5.13), did not suggest other information not found already with ANOVA. It is worth noticing that most interaction dot-line plots were parallel/overlapping lines, which makes it very difficult to spot differences or simply indicates non-significance.

		Mean	**Std. Dev.**	**LTB**
Full factorial design	**Std. Dev.**	0.922		
	LTB	0.668	0.473	
	Peak	0.909	0.991	0.471
Taguchi array	**Std. Dev.**	0.888		
	LTB	0.676	0.421	
	Peak	0.877	0.994	0.402

Table 5.5 Correlation (Pearson) matrix for main responses (OOBF problem).

		Source	DF	Seq SS	Adj SS	Adj MS	F-value	P>F
Peak value	Full Factorial	Main Effects	5	7323715173	7323715173	1464743035	22.56	0.001
		2-Way Interactions	10	3408385871	3408385871	340838587	5.25	0.027
		3-Way Interactions	10	2124865442	2124865442	212486544	3.27	0.08
		Residual Error	6	389521852	389521852	64920309		
		Total	31	13246488337				
	Taguchi	Main Effects	5	3716807433	3716807433	743361487	1.72	0.219
		Residual Error	10	4332505827	4332505827	433250583		
		Total	15	8049313259				
Mean	Full Factorial	Main Effects	5	1738915150	1738915150	347783030	58.51	0
		2-Way Interactions	10	458695752	458695752	45869575	7.72	0.011
		3-Way Interactions	10	133676355	133676355	13367635	2.25	0.167
		Residual Error	6	35665941	35665941	5944324		
		Total	31	2366953198				
	Taguchi	Main Effects	5	874213501	874213501	174842700	4.76	0.017
		Residual Error	10	367344996	367344996	36734500		
		Total	15	1241558496				
Standard Deviation	Full Factorial	Main Effects	5	1040649438	1040649438	208129888	20.96	0.001
		2-Way Interactions	10	523471312	523471312	52347131	5.27	0.027
		3-Way Interactions	10	321045583	321045583	32104558	3.23	0.082
		Residual Error	6	59577242	59577242	9929540		
		Total	31	1944743575				
	Taguchi	Main Effects	5	521530169	521530169	104306034	1.63	0.24
		Residual Error	10	641273310	641273310	64127331		
		Total	15	1162803479				
Larger-the-Better	Full Factorial	Main Effects	5	695.091	695.091	139.018	9.00E+03	0
		2-Way Interactions	10	1.313	1.313	0.131	8.85	0.007
		3-Way Interactions	10	1.684	1.684	0.168	11.35	0.004
		Residual Error	6	0.089	0.089	0.015		
		Total	31	698.177				
	Taguchi	Main Effects	5	349.943	349.943	69.9886	388.5	0
		Residual Error	10	1.801	1.801	0.1801		
		Total	15	351.744				

Table 5.6 ANOVA model fitting test for all responses from full factorial and Taguchi arrays (OOBF with RotChr off).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F-value	P>F	F-value	P>F	F-value	P>F	F-value	P>F
Full factorial	Main Factors	POPSIZE	167.7	0	41.61	0.001	4.60E+04	0	43.84	0.001
		MAXGEN	92.09	0	35.05	0.001	107.97	0	39.86	0.001
		XOVER	0.17	0.692	0.14	0.722	130.78	0	0.31	0.597
		TOURN	4.35	0.082	3.59	0.107	124.87	0	6.53	0.043
		MUTPRO	28.21	0.002	24.41	0.003	0.41	0.547	22.27	0.003
	Interactions	POPSIZE*MAXGEN	22.75	0.003	3.57	0.108	0.61	0.463	2.36	0.176
		POPSIZE*XOVER	13.58	0.01	17.3	0.006	15.35	0.008	19.79	0.004
		POPSIZE*TOURN	0.21	0.661	0.11	0.747	0.66	0.447	0.1	0.76
		POPSIZE*MUTPRO	1.47	0.271	0.22	0.656	5.53	0.057	0.67	0.444
		MAXGEN*XOVER	6.65	0.042	5.93	0.051	4.25	0.085	4.17	0.087
		MAXGEN*TOURN	0	0.95	0.27	0.623	7.13	0.037	0	0.974
		MAXGEN*MUTPRO	10.49	0.018	2.98	0.135	3.56	0.108	2.4	0.172
		XOVER*TOURN	0.05	0.835	0.03	0.866	40.78	0.001	0.24	0.645
		XOVER*MUTPRO	13.42	0.011	14.68	0.009	7.6	0.033	14.78	0.009
		TOURN*MUTPRO	8.54	0.027	7.62	0.033	3.03	0.132	8	0.03
		POPSIZE*MAXGEN*XOVER	0.52	0.497	0.46	0.522	1.22	0.312	0.83	0.397
		POPSIZE*MAXGEN*TOURN	1.4	0.282	2.64	0.155	1.03	0.349	3.29	0.119
		POPSIZE*MAXGEN*MUTPRO	4.59	0.076	1.52	0.263	3.24	0.122	0.75	0.42
		POPSIZE*XOVER*TOURN	0.41	0.544	0.01	0.94	99.11	0	0.09	0.77
		POPSIZE*XOVER*MUTPRO	0.13	0.735	2.14	0.194	0.49	0.512	4.2	0.086
		POPSIZE*TOURN*MUTPRO	8.13	0.029	6.43	0.044	1.28	0.301	6.57	0.043
		MAXGEN*XOVER*TOURN	0.03	0.871	0.67	0.446	1.28	0.301	1.69	0.241
		MAXGEN*XOVER*MUTPRO	2.63	0.156	3.42	0.114	1.22	0.312	2.75	0.148
		MAXGEN*TOURN*MUTPRO	2.68	0.153	11.84	0.014	4.01	0.092	11.79	0.014
		XOVER*TOURN*MUTPRO	1.97	0.21	3.2	0.124	0.61	0.463	0.76	0.416
		Error	35665941		59577242		0.089		389521852	
Taguchi array	Main Factors	POPSIZE	14.41	0.004	3.04	0.112	1927.14	0	2.88	0.121
		MAXGEN	6.72	0.027	2.19	0.17	4.5	0.06	2.79	0.126
		XOVER	0.03	0.864	0.2	0.666	4	0.073	0.34	0.572
		TOURN	0.01	0.926	0.05	0.83	6.84	0.026	0.17	0.692
		MUTPRO	2.62	0.136	2.66	0.134	0.03	0.856	2.41	0.152
		Error	367344996		641273310		1.801		4332505827	

Table 5.7 Summary of factor/level analysis for the OOBF with RotChr off.

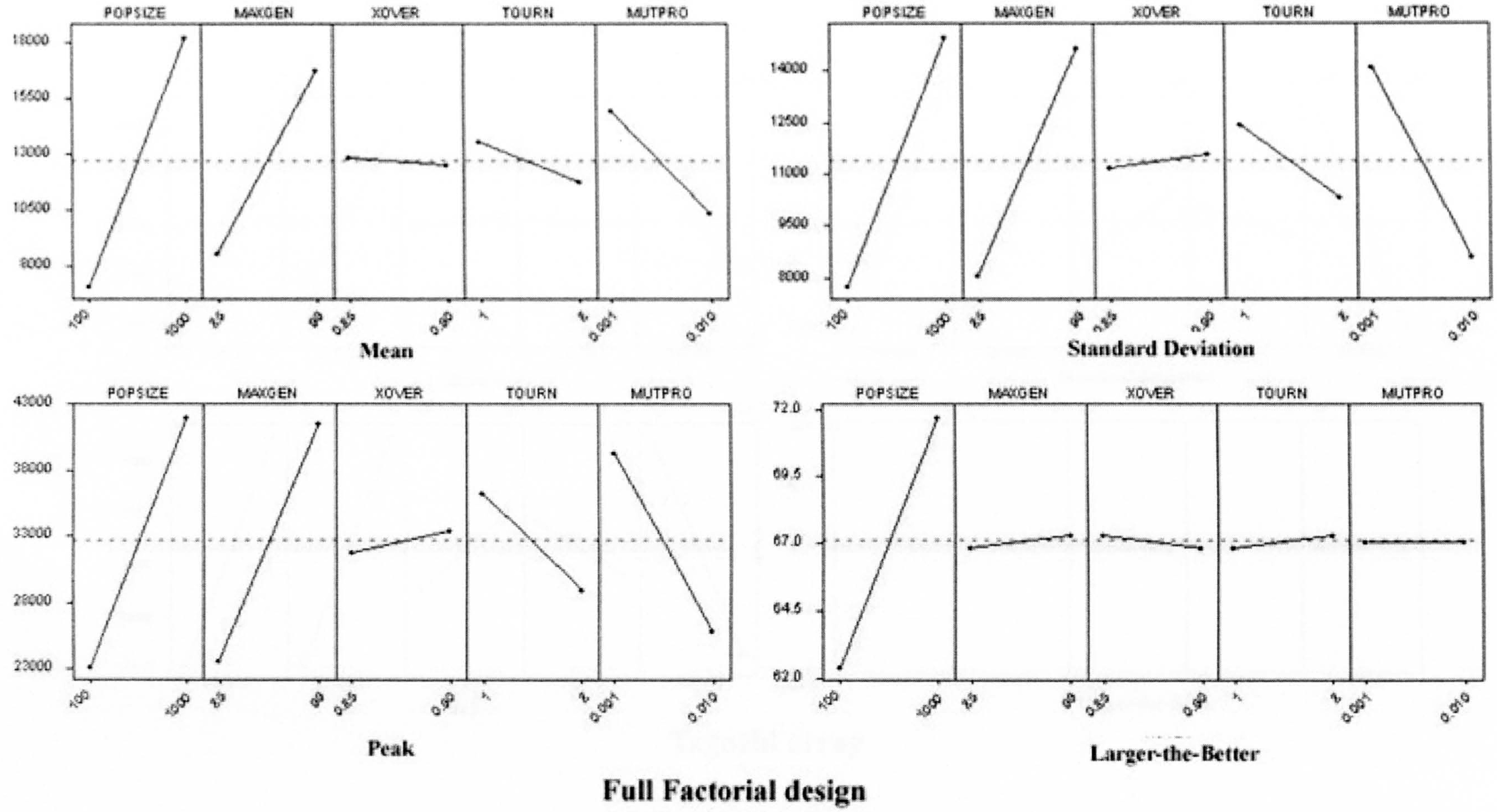


Fig. 5.5 Dot-line plots for main factor effects – full factorial design (OOBF problem with RotChr off).

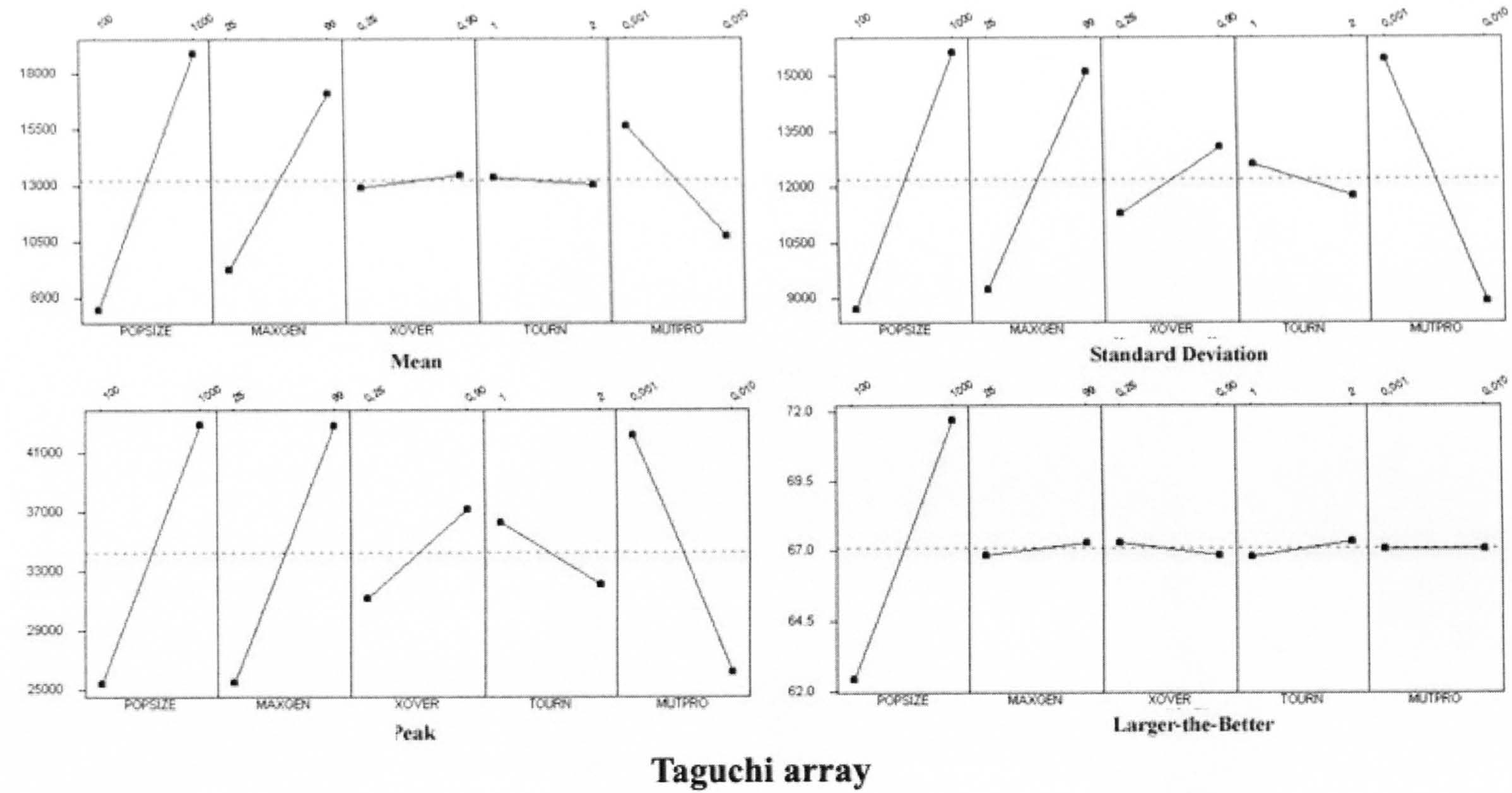


Fig. 5.6 Dot-line plots for main factor effects - Taguchi array (OOBF problem with RotChr off).

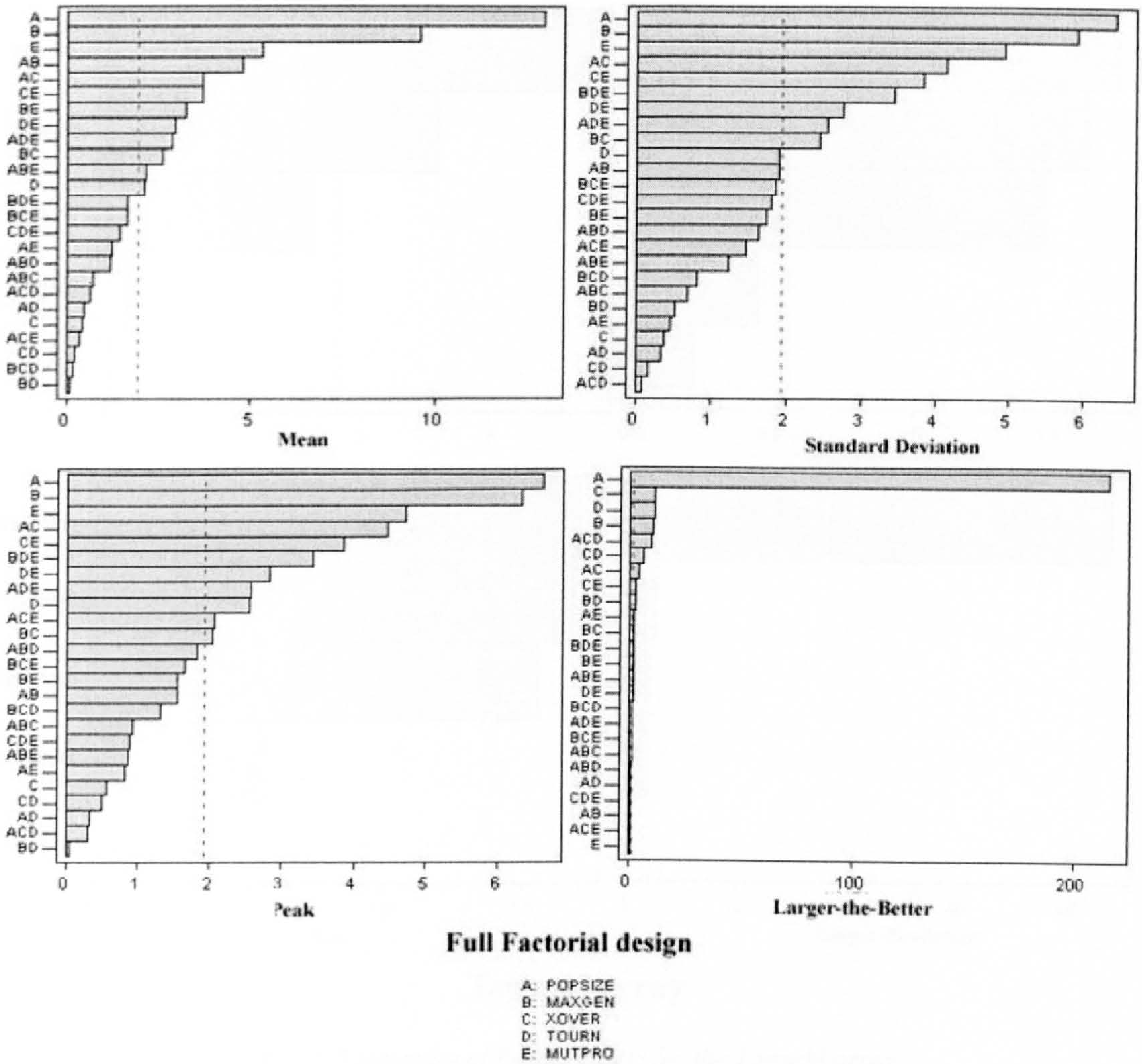
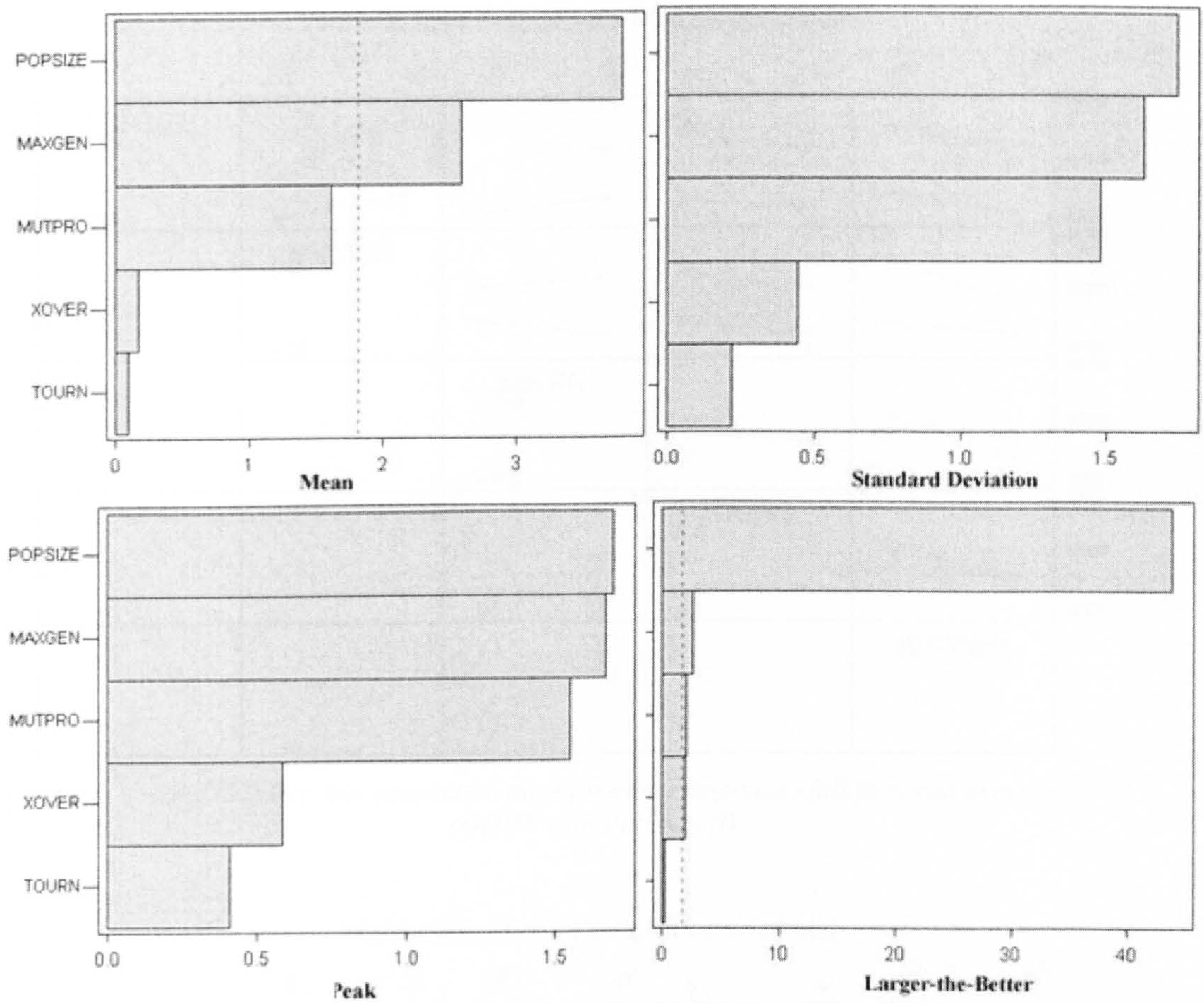


Fig. 5.7 Summary of Pareto charts for the full factorial design (OOBF problem with RotChr off)(Alpha=0.10)



Taguchi array

Fig. 5.8 Summary of Pareto charts for the Taguchi array (OOBF problem with RotChr off)(Alpha=0.10).

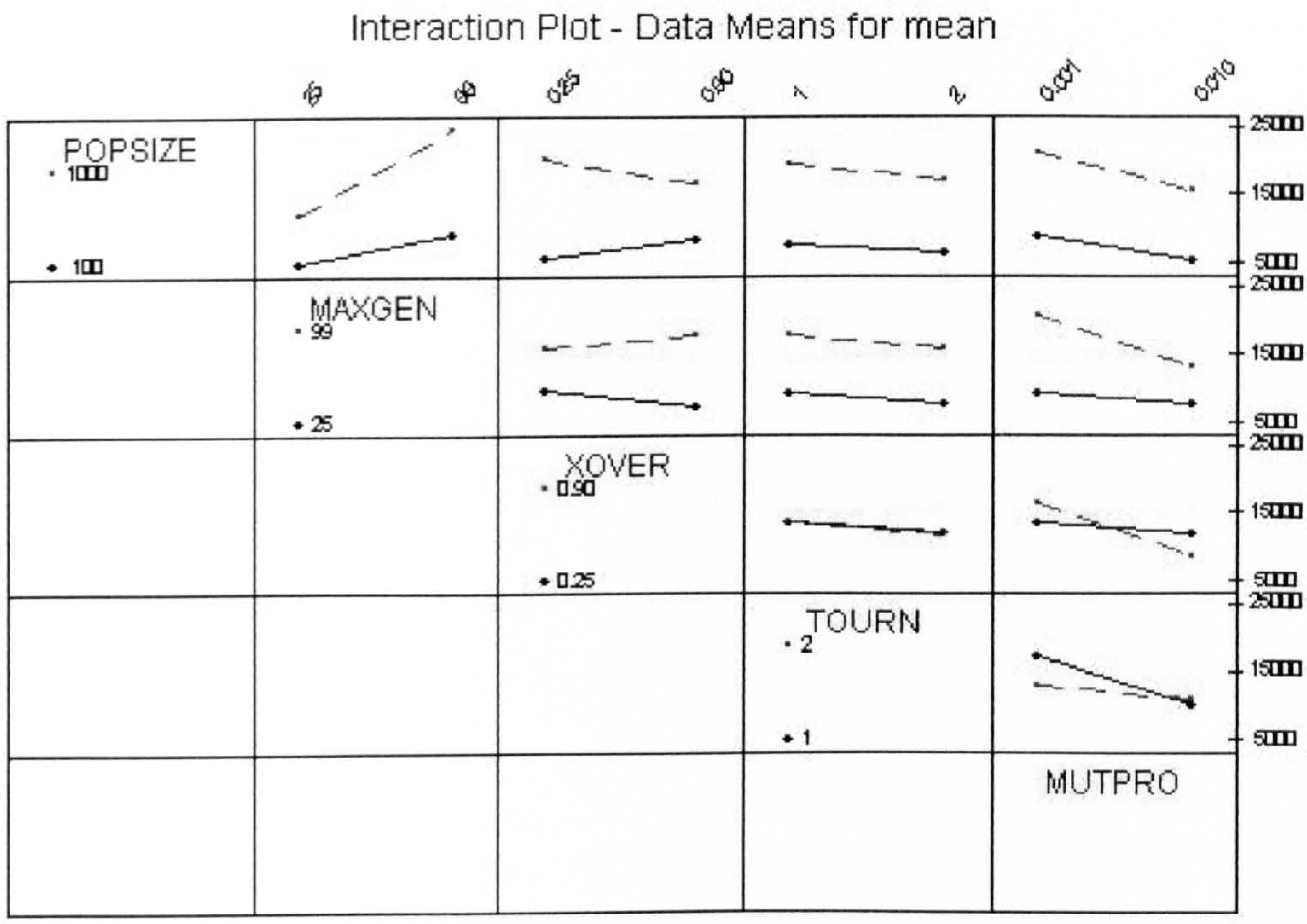


Fig. 5.9 Dot-line interaction plots for mean response –full factorial array (OOBF with RotChr off).

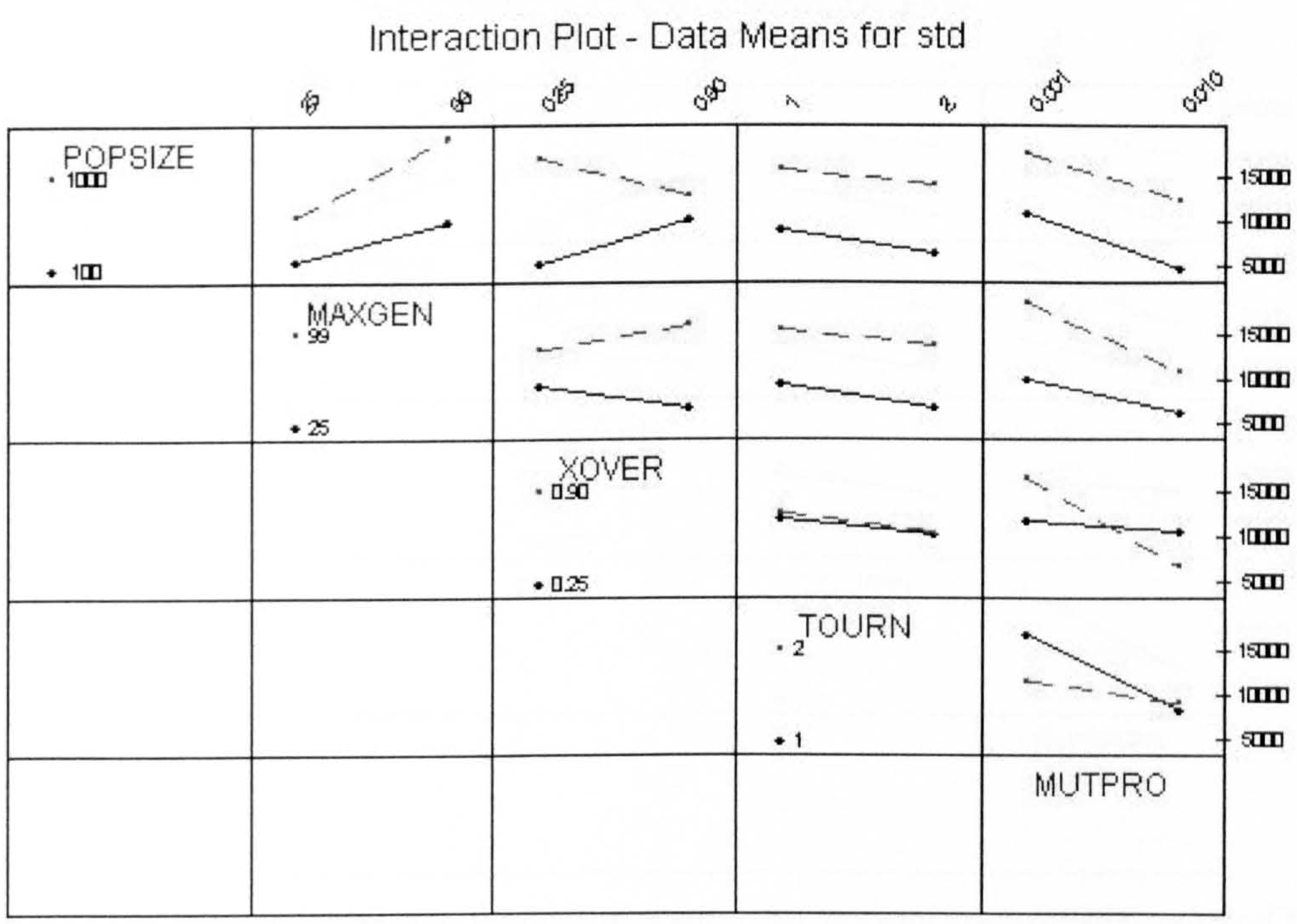


Fig. 5.10 Dot-line interaction plots for standard deviation response – full factorial array (OOBF with RotChr off).

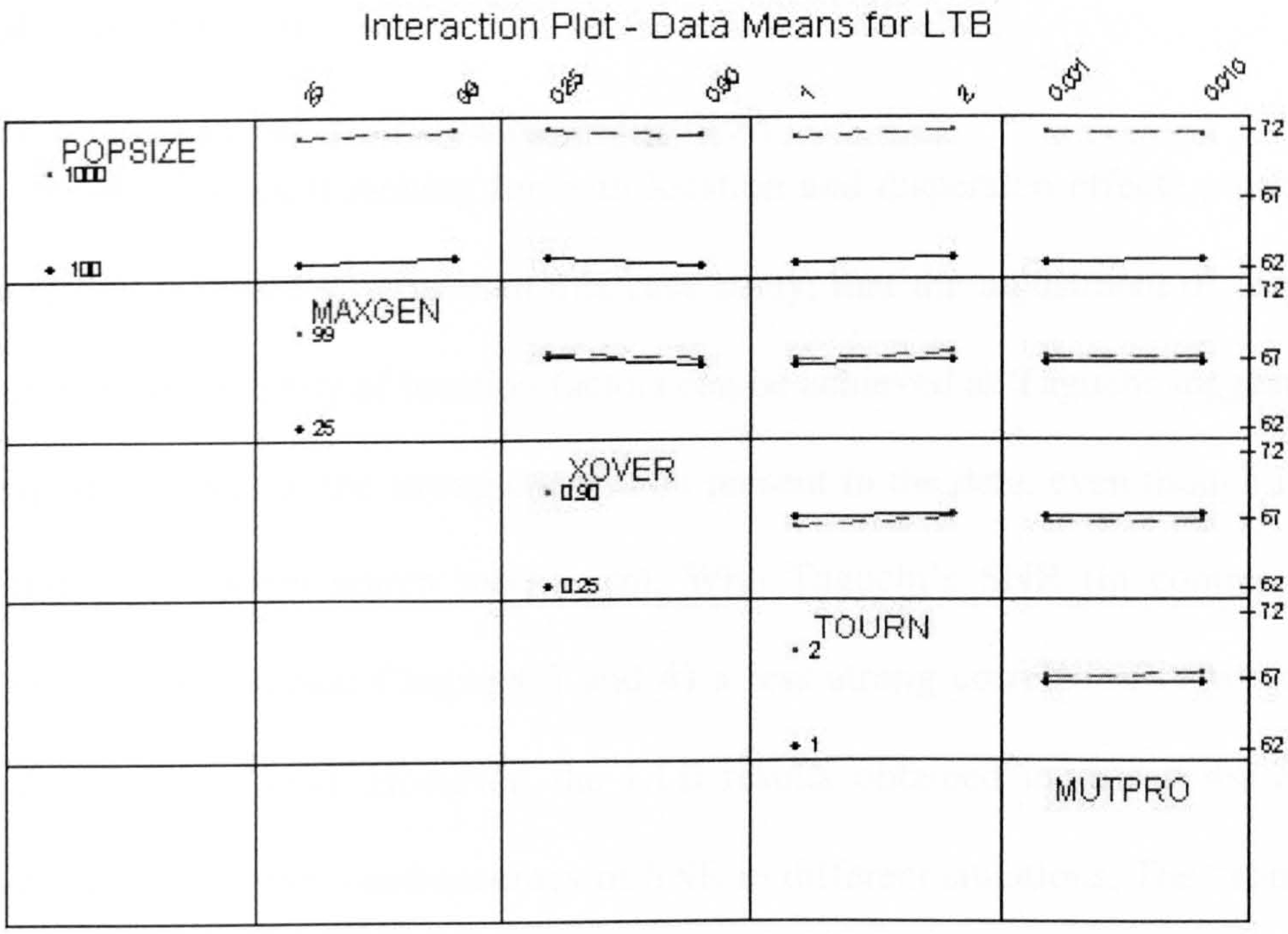


Fig. 5.11 Dot-line interaction plots for Larger-the-Better response – full factorial array (OOBF with RotChr off).

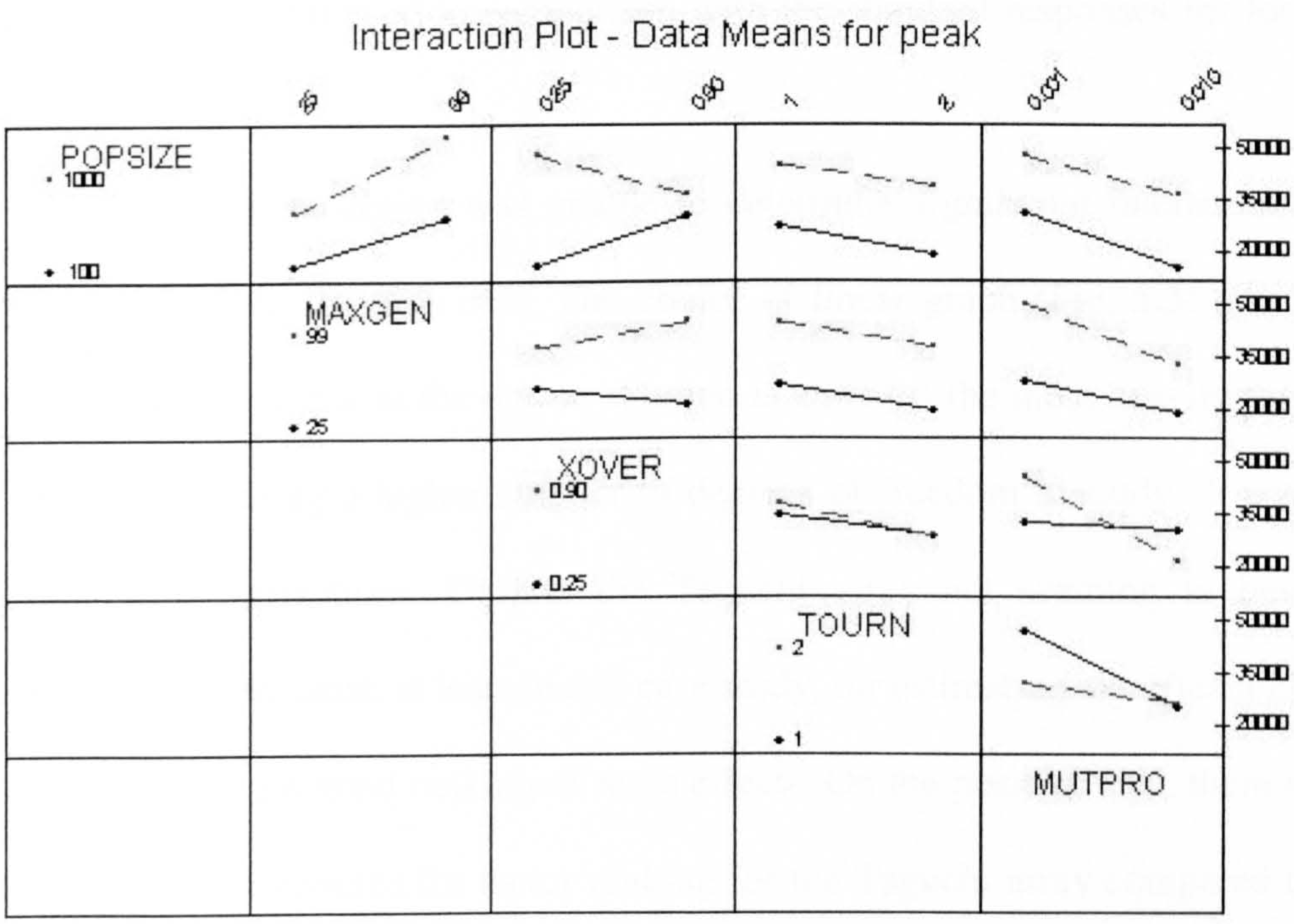


Fig. 5.12 Dot-line interaction plots for Peak response – full factorial array (OOBF with RotChr off).

5.4 Discussion

5.4.1 Statistical methods investigation

The identical ranking for both location and dispersion effects proves once more that is unlikely, at least in this case study, that the adjustment of dispersion factors independently of location factors can be achieved as Taguchi suggests. This may be an effect of the strong correlation present in the data, even though it was a result of a random search mechanism. With Taguchi's SNR (in contrast to the previous case studies: Chapters 3 and 4) a less strong correlation between mean and LTB was found. However, the LTB results obtained increased the concern over the effectiveness and accuracy of SNR in different situations. The "abnormal" percentage contribution found for LTB (Fig. 5.13) indicated that its modelling capabilities looked flawed in comparison with the standard responses for location and dispersion.

The Taguchi design was unable to determine significant interaction (and some main) effects for this case. The choice of linear graph (Fig. 5.3) may have some influence on this as the option selected is amongst the most heavily featured of its type, requiring a higher number of degrees of freedom to study all possible second-order interactions. Despite the Taguchi array not seeming to have an acceptable performance, at least in this case study, for estimating significant effects it is still able to get good ranking of main effects. On the positive side, there was a similarity in performance for factor ranking for the Taguchi array compared to the full factorial design. The results backed this (Fig. 5.5, 5.6 and 5.13) as plots followed the same trend as for the full factorial design. Besides these results for factor/level analyses on the normal data set (RotChr off), other results for the remaining twelve data sets featuring RotChr and summarised in a frequency table (Appendix D3) gave similar results.

5.4.2 GA investigation

Outcomes from the correlation tests indicated that certain data and/or response behaviour and relationships influenced results in this case study, eg similarities among results obtained for ANOVA and dot-line plots. ANOVA tests and dot-line plots identified some non-significant main factors whose effects were overwhelmed by stronger main factors. In most cases, determining the percentage contribution of main factor effects on responses may offer additional information not easily spotted on dot-line plots. Graphical representations ranking the order of influence for main factors (as well as interactions) on all responses, based on F-values from the GLM tests, were used to look for that additional information (Fig. 5.13). Ranking was straightforward thanks to the correlations, as mean, standard deviation and peak value all suggested the same ranking. Population size, number of generations, mutation probability, tournament selection and crossover probability was the suggested order of importance. This main factor ranking supports the best design settings suggested in the previous section (Section 5.3.5) and confirms that whatever level of crossover probability is chosen should not affect the responses as it counts for less than 1% of the effects in all cases (Fig. 5.13). Therefore, selection of the best design setting may be very sensitive due to the large effects of the most significant factors. For instance, the best design setting corresponds in the full factorial array to the run with the highest fitness (run 26) (Table 5.8), which means higher population size (1000) and number of generations (99), lower mutation probability (0.001), higher ratio of tournament size/winners (2/1) and whatever crossover probability is selected. A run with such settings is not included within the Taguchi array. The absolute lack of importance of crossover probability is a surprising result, in contradiction to a number of previous studies (coupled with the fact that some significant second and third-order interactions involved crossover probability), leaving some doubts as to whether this factor should be considered not significant despite the evidence suggesting otherwise.

The top five solutions found with the normal data set (RotChr off) (Table 5.8) suggested a best fitness value of 74317.5 with a chromosome starting with the gene 2 (three of the top-five solutions started with this gene). The data set with RotChr on with a chromosome 2 locked in the first string location suggested a peak value of 74560.8 which was an improvement in relation to the original data set (Fig. 5.14). This chromosome was within a region with the best fitness found if the whole thirteen data sets were combined (Fig. 5.14). There is, however, no evidence that RotChr (on or off) offers any improvement. In fact, using different starting genes should not in principle affect the GA outcome and those results indicate a lack of robustness with the method.

Overall optimal solution (population size of 1000, 99 generations, mutation probability of 0.001, tournament size/winners of 2/1 and a crossover probability of 0.9) found for the OOBF was found for a chromosome whose first gene was 3 giving a maximum fitness of 76173.2. This result was less than 5% off the true optimum value, which was 80643 (an equivalent OOBF of 1.24036E-5 $N \bullet s^2/rad^2$ corresponding to the chromosome: 3-1-4-2-10-9-7-6-11-8-5-12) (Skou, 1996). This best result was obtained with the best design settings (optimised parameters) suggested in this case study. However, different results were obtained for different starting seed values (Fig. 5.16), which indicate that results may be seed dependent and that the GA is not as robust as is often claimed. For this reason, taking into consideration the random nature of GAs, it is advisable to always run more than one seed.

Comparison of optimal design settings found for both cases of RotChr (on and off) suggests that these may be the best possible settings to be found with this GA and problem. These best possible settings seem to agree with what common sense dictates:

- Higher population size provides a wider solution space, increasing the probability of finding better solutions within the same "period". In contrast, most researchers (Section 5.2) have recommended mid-low population sizes, though what "mid-sized" means may be quite subjective and problem dependent.
- Higher number of generations increases the length of the evaluation period, giving more opportunities for better chromosomes to evolve and yield better solutions. Again, most investigations (Section 5.2) suggested lower number of generations though it is believed that those suggestions relied heavily on resource constraints. On the other hand, it is reasonable to require a higher number of generations to let a big population evolve.
- Lower mutation probability allows having enough diversity within the population without transforming it into a plain random search algorithm (Cao and Wu, 1997). This recommended setting is in complete agreement with

what has been suggested in the literature (eg De Jong, 1975; Goldberg, 1989; Salomon, 1996b; Zuo, 1997).

- A very slight tendency to prefer higher crossover probability (optimal solution for RotChr on) has been found if comparing both optimum solutions (from RotChr on and off). However, this may be due to an effect of the random search characteristics of GAs. Therefore, choosing/recommending a value of crossover probability has been found unimportant (at least in the present case), unlike for many researchers (Section 5.2) who have hinted it as extremely significant.

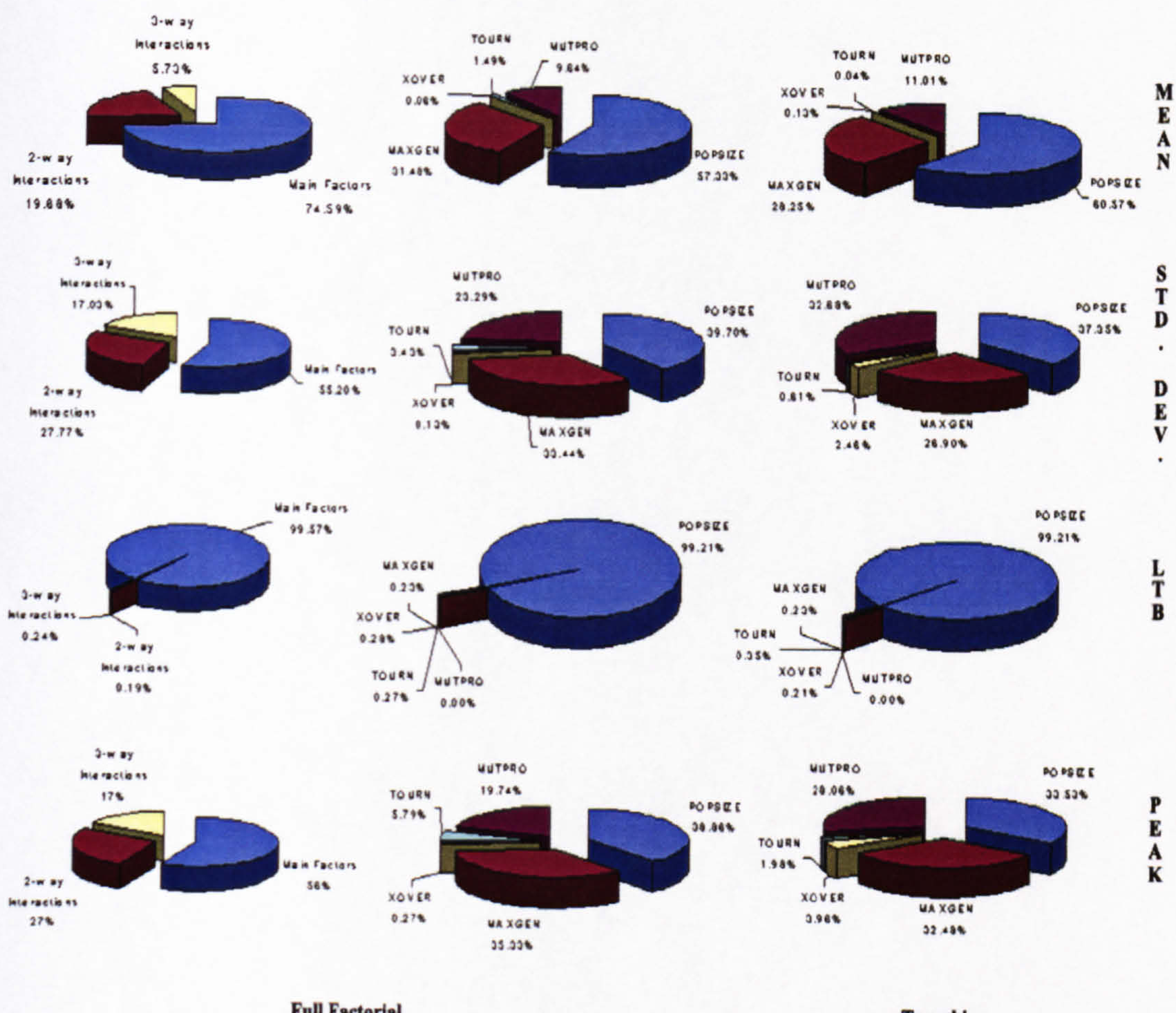


Fig. 5.13 Fitness percentage contribution of the effects for full factorial and Taguchi arrays (RotChr off).

	Full factorial					Taguchi				
Rank	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Run	26	21	5	13	31	8	15	13	14	9
Seed	0.417	0875	0.95	0.417	0.417	0875	0.95	0.417	0.025	0.025
Fitness	74317.5	72987.9	71657.5	51962.5	51962.5	72987.9	71657.5	51962.5	51204.1	51192.3
Chromosome	4	3	1	9	9	3	1	9	7	10
	1	1	3	1	1	1	3	1	8	4
	3	4	2	3	3	4	2	3	12	2
	12	2	5	12	12	2	5	12	4	5
	5	10	9	10	10	10	9	10	1	9
	8	9	11	5	5	9	11	5	9	8
	11	7	6	8	8	7	6	8	2	1
	6	6	7	4	4	6	7	4	3	11
	7	11	8	11	11	11	8	11	10	7
	9	8	10	6	6	8	10	6	5	6
	10	5	12	7	7	5	12	7	6	3
	2	12	4	2	2	12	4	2	11	12

Table 5.8 Top five solutions for the OOBF problem (RotChr off) for full factorial and Taguchi arrays.

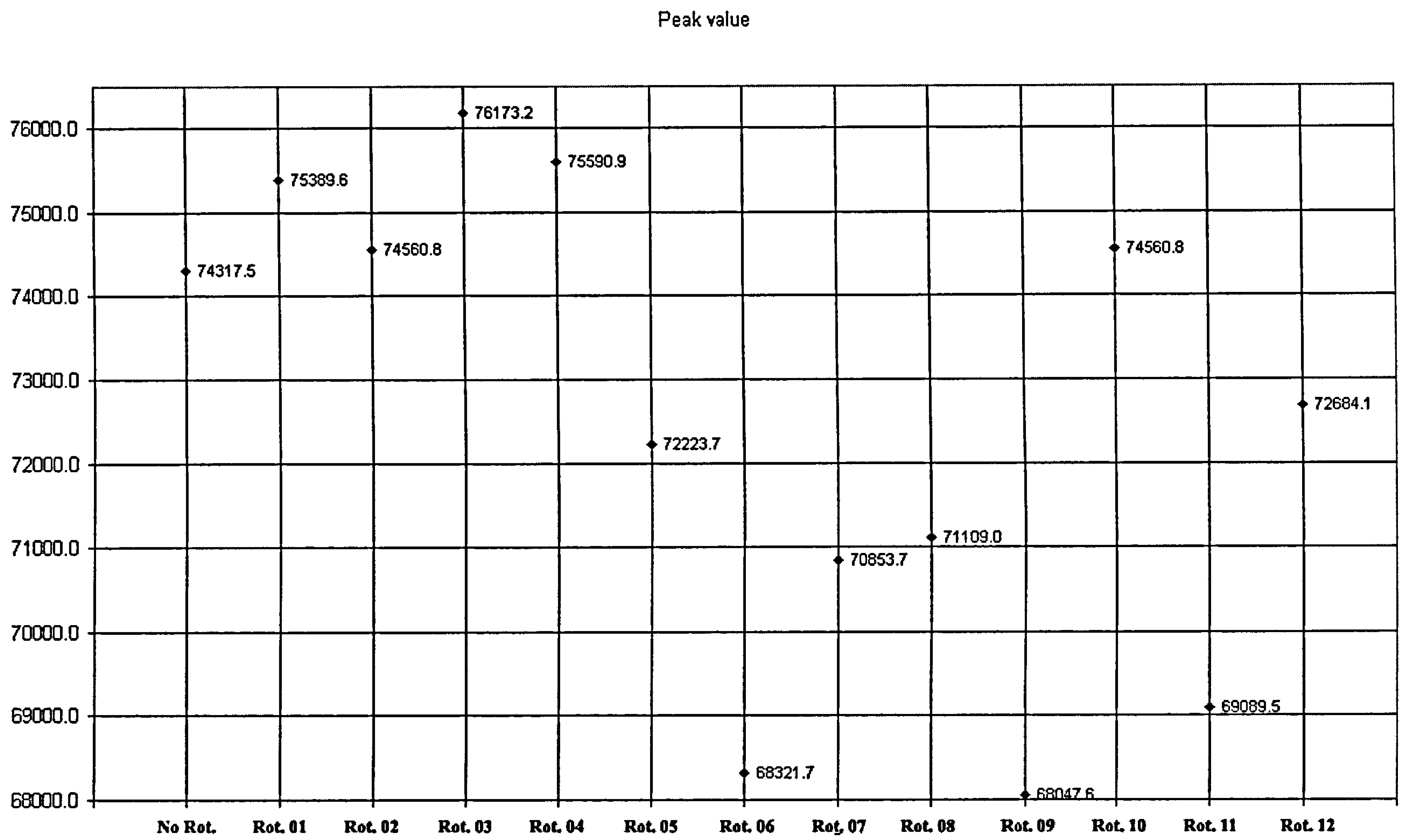


Fig. 5.14 Maximum fitness plot for the OOBF problem (all data sets).

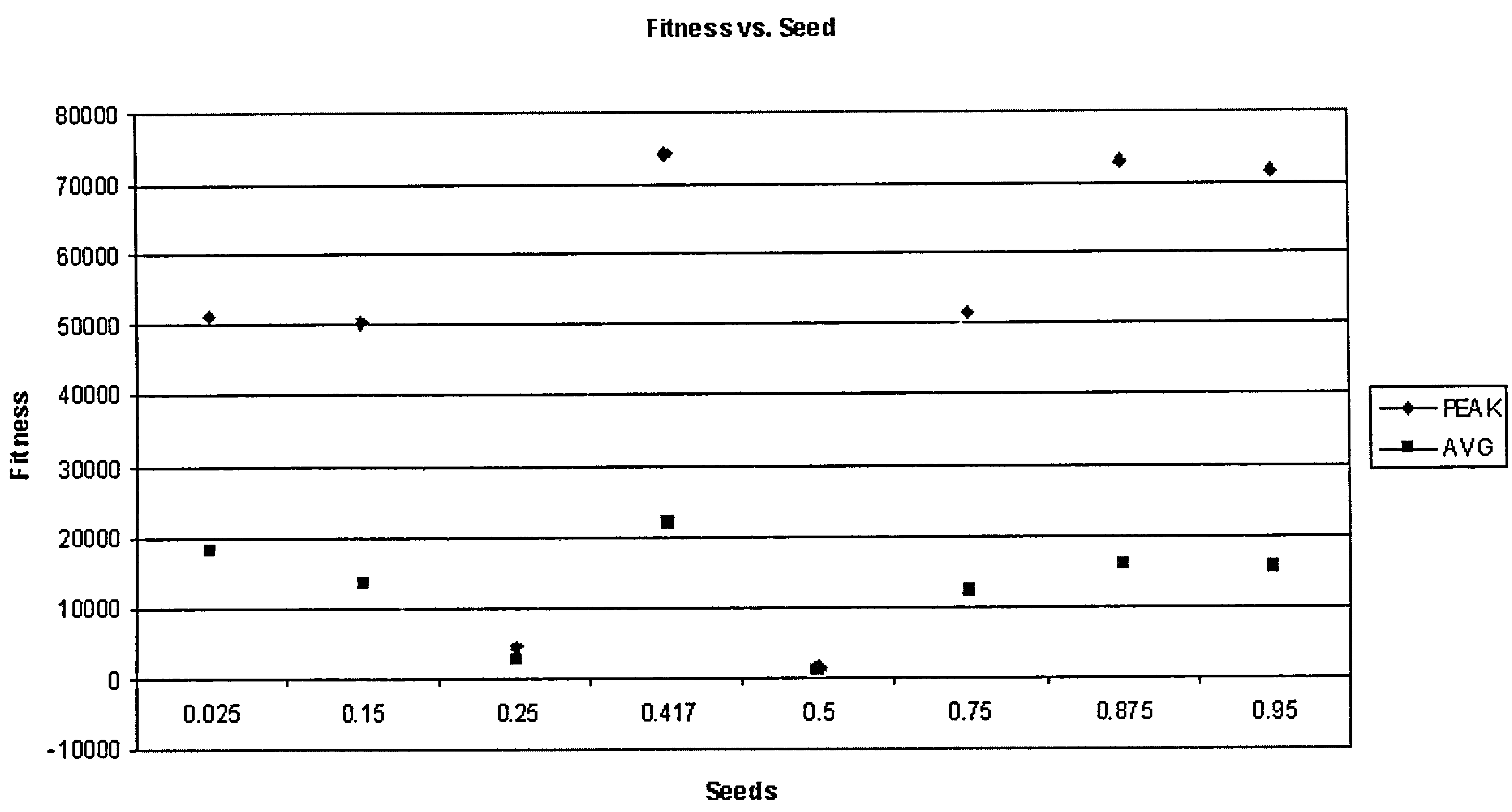


Fig. 5.15 Fitness performance against seed values for the OOBF problem (RotChr on → all seeds).

5.5 Recommendations for further study

In view of the above results with different seeds and different genes (RotChr off or on) suggestions made by Povinelli and Feng (1999), on implementing a storage system/table to keep records of the latest evaluated chromosomes and their fitnesses to enhance GA performance, offers an interesting path for further study. Such hashing operations may also be implemented in a form of parallel GAs using more than one evaluation mechanism separated from the remaining processes and enhanced with a custom queuing/assignation algorithm for reducing and/or alleviating the "bottleneck". However, parallel GAs transfer most of the basic GA mechanisms (particularly selection, crossover and mutation) into multiple threads. Therefore, the approach suggested in this work to optimise and maximise each one of those threads remains appropriate.

Through the application of this approach based on the application of DoE, many issues surrounding the application of GA to several problem types can be addressed. Further investigations should aim at using this approach to solve general issues such as:

- Determination of appropriate ranking and scaling methods for maximising GA performance.
- Estimation of the influence of selection mechanisms (ie tournament, roulette wheel) and some other GA operators (ie crossover, mutation) on achieving specific convergence rates.
- Determine appropriate stopping/termination criteria for achieving a desired solution quality.

In addition to addressing these issues, a thorough study of the convergence rate as a main response is recommended for further investigation. An implementation applying the framework applied in this case study would be helpful to identify interrelationships surrounding convergence and other GA parameters.

Chapter 6

Design of Experiments techniques applied to tool analysis

6.1 Objectives

The study of complementary techniques and tools that may enhance the effectiveness of Taguchi methods could bring benefits for the "non-experts" at whom Taguchi aims his methodology, who may be seeking value from their experiments without the difficulties involved in more complicated conventional statistical techniques. Determining the effective combination of other existing techniques with Taguchi methods may help experimenters without a strong background in statistics to use Taguchi methods in a more robust manner, as suggested by Taher (1995) in previous research.

Four case studies are used to investigate some of these issues in an attempt to provide guidance to engineers seeking to exploit Taguchi tools. These four case studies (Table 6.1) involved two different problem types: metal removal, ie turning (Taher, 1995) and milling (Chapter 3), and simulation environments, ie traffic signal control (Chapter 4) and simple genetic algorithms (Chapter 5). The turning case study has been discussed in part previously (Taher and Anderson 1993a and 1993b; Taher, 1995) whilst the other three have been discussed in previous chapters (Chapters 3 to 5). The main objective in this Chapter was to study the effectiveness and interoperability of Taguchi and non-Taguchi tools for DoE. The study would not be complete without providing answers, within the industrial application context, to basic questions such as:

(i) Are the Taguchi arrays appropriate in practice? Are there effective ways to use Taguchi arrays?

(ii) Is SNR an appropriate metric to measure dispersion?

(iii) Is it actually possible to find parameters which reduce dispersion without affecting the mean as required by Taguchi's approach?

(iv) Are repetitions necessary? If so, how many? Would the number of repetitions be influential in a particular design?

(v) Does it help to bring in other statistical ideas like data transformation or robust statistics?

Case / ***Objective***	**Reference array**	**Taguchi arrays**	**SN ratios**	**Controllable factors**	**Noise factors**
Milling / *Surface finish*	Full factorial	L_{16}	STB	Tool speed Workpiece speed Coolant use Direction of cut Depth of cut Number of cuts Tool type	
Turning / *Surface finish*	Full factorial	L_{18}	STB	Tool shape Tool type Feed rate Spindle speed Coolant rate	
Traffic Flow / *Delay*	Full factorial	L_{32}	STB	Controller Type	Speed distribution Vehicle mix Profile slopes (3 branches) Profile magnitudes (3 branches)
Genetic Algorithms / *Parameter optimisation*	Full factorial	L_{16}	LTB	Crossover probability Mutation probability Number of generations Population size Tournament size	

Table 6.1 Case studies for investigation.

6.2 Background to the case study

The way Taguchi packaged and "sold" his basic tools (orthogonal arrays, linear graphs, Loss Function, SNR and interaction tables) to make them attractive to non-statisticians was the key for his success in industry (Condra, 1995). As Taguchi methodologies concentrate on variation reduction (Lochner and Matar, 1988, 1990), most critics focus not only on his statistical foundations (in fact, the majority of critics do) but also on whether variation reduction is still achievable despite such imperfections. From a practical perspective, the point is not whether variation reduction can be achieved through Taguchi methodologies but how it can be achieved in a reliable and consistent way, as most of his basic tools have been successfully applied within the industrial context. Suggestions that, despite the importance of variation reduction, Taguchi's use of experimental design is inappropriate in many ways can be found in the literature (eg Phadke, 1992; Nair, 1992; Kackar, 1985). This can cause some scepticism among engineers about the appropriate use of his approach because Taguchi's three main tools (Loss Function, SNR and Taguchi arrays) are among those raising most concern among statisticians (Section 2.2).

Since the debate has been around for some time now, solutions and/or alternatives have been proposed for overcoming some of these issues. Logothetis and Wynn (1989) suggested that approaches modifying Taguchi's methodologies to make them consistent with basic statistical principles (so further controversies would be wiped out) should be the path to take. For instance, Robinson (1993) suggested two changes to Taguchi's packaging of fractional factorial designs: the idea of confounding tables and a modification of Taguchi's linear graphs (which tends to encourage the use of a different set of linear graphs and thereby to encourage the use of higher resolution designs). Confounding tables proposed by Tsui (1988) can be a good addition, though knowing where to find interactions without knowing their real effect may not be helpful at times. Within a similar context, Phadke and Taguchi (1987) and Phadke (1989) proposed guidelines for selecting appropriate quality characteristics and SN ratios. However, they recognised that finding quality characteristics that meet all of these guidelines is sometimes difficult (Phadke, 1992) and some of the guidelines they proposed have been questioned (Wu, 1992).

Application of Taguchi tools is based on some important assumptions for his orthogonal arrays, SNR, variation control and interaction handling. Taguchi's experiment designs (based on standard Fractional Factorials) are assumed to be as effective as traditional/conventional arrays (eg full or fractional factorial), because in industrial problems the presence and incidence of interactions on the control factors is assumed to be of secondary importance and, moreover, third and higher order interaction effects are thought to be unlikely (Taguchi, 1987; Ross, 1988). It is also assumed that the control of both location and also dispersion effects may be done efficiently through joint modelling techniques such as SN ratios (Taguchi, 1987). However, evidence of strong correlations between SN ratios and mean has been identified by Taher (1995), whether or not mean and standard deviation were correlated. This indicates that SN ratios are not the most appropriate metric for measuring dispersion, so better joint-estimation of location and dispersion may be required (Taher and Anderson, 1993b). Approaches have been suggested to this joint modelling problem (eg Vining and Myers, 1990; Box, 1988; Kackar 1985). Finally, conventionally there are two routes to improving quality levels: reducing variation or tightening tolerances. Taguchi (1987) favours the former over the latter and the key to his robust design approach is the assumption that there is the possibility of finding controllable parameters within the experiment which reduce dispersion without affecting location as much. For cases where variation (eg standard deviation) correlates with location (eg mean), as in previous chapters (summary in Table 6.2), then this is clearly a questionable assumption.

Case study	SN ratio	Correlations		
		SN to mean	SN to Std. Dev.	Mean to Std. Dev.
Milling	STB	-0.93	-0.93	0.98
Turning	STB	-0.94	-0.49	0.39
Traffic Flow	STB	-0.98	-0.90	0.89
GAs	LTB	0.67	0.47	0.92

Table 6.2 Summary of correlation tests on the four case studies (Data from full factorial arrays).

6.3 Evaluation of the case studies

The idea of using DoE itself to investigate DoE techniques such as Taguchi's does not seem to have been suggested previously, certainly not in the Taguchi literature. Raw data from four case studies was reorganised and reanalysed in this context to compare some Taguchi and non-Taguchi tools. Making use of standard DoE techniques, these tools were tested for their "robustness" and usability under different circumstances. According to the framework methodology already suggested (Section 3.3) and applied, this starts with problem definition, in this case to determine the significance and compatibility of some statistical tools with Taguchi tools for controlling location and dispersion effects. The decision on which tools to choose relies on a survey of the advantages and disadvantages of Taguchi methodologies (Section 2.4). This was reinforced with the addition of particular tools that have been suggested by statisticians to overcome the perceived deficiencies of some basic Taguchi tools.

The brainstorming phase should start by considering those tools pointed out in the literature (Section 2.4) complemented by those suggested by Taher (1995).

6.3.1 Experimental design phase

Being a main topic in this work, it is an obvious choice to select array types as a possible factor. Taguchi arrays should be a must in this case as one of the most acknowledged Taguchi tools (Wu, 1992; Chan and Ho, 1993; Lyon *et al,* 1991). There are many "conventional" arrays in DoE that can suit most situations, from full factorial, through fractional factorial, to Central Composite designs, and that Taguchi arrays can be compared with. A good opportunity to appreciate the benefits from less experimentation (fewer runs) may be by comparing Taguchi arrays with full factorial arrays. Though this has already been done by comparing the outcome from both arrays in some case studies (Taher, 1995) and throughout this work, this provides an opportunity to benchmark them against other choices within the DoE framework.

Other major Taguchi tools are SNR and linear graphs. Notice that SNR may have a dual role, either as a tool for assessing performance (through measuring location and dispersion) or as a plain response, depending on the goal (that is the way it has been used in the previous case studies). In the case that SNR are used for their modelling capabilities, another tool which has not been exploited by Taguchi is data transformation (Logothetis and Wynn, 1989). Data transformations have been suggested by statisticians as a better alternative to SNR (Box, 1988; Rowlands, 1995). From the "novel" front of statistical methodologies, robust statistics have emerged as a set of potentially more reliable estimators for location and dispersion (Section 2.3.4). Statistical tools such as randomisation, blocking, etc, (Ross, 1988; Mead, 1988; Montgomery, 1991) are fundamental for any designed experiment.

The responses for investigation are those utilised in each of the separate case studies as they are the sources of data. Due to each case study having particular responses and objectives, the only common metrics are those for measuring location and dispersion effects. Thus, mean, standard deviation and SNR were the responses for this study. The initial group of factors suggested during the brainstorming session was reduced in number in order to shrink the size of the experiment. The final selection considered four factors: Transformations, Method, Repetitions and Statistics (Table 6.3).

Since SNR is one of the three main responses, selecting transformation would allow study of the effects of this on dispersion control as well as having a practical look at it since it has been tipped as a good replacement for SNR. Several options may be available for the different levels the transformation factor may take, eg to help establish differences between using data without transformations, data with optimal transformation using the Box-Cox method (Montgomery, 1991) and using any other transformation different from optimal. Amongst these options, just two were used at this stage (raw data and optimal transformations) so the overall array was kept with two levels. None of the case studies examined previously (Chapters 3 to 5) made use of transformations with only the raw data utilised for analysis. The method factor included the main comparison of this study featuring both full factorial and Taguchi arrays as levels, which have been systematically used and applied throughout this work. Note that these full factorial arrays are the arrays used to obtain raw data from each case study and should not be confused with the full factorial array for this comparison (Table 6.3).

With the repetitions factor, the aim was to determine the appropriate number of repetitions (or replications) (Section 2.3.2) recommended for achieving variance reduction within the experiment. Determination of the levels in Table 6.3 was limited by the case studies (Table 6.4), which varied between four and eight repetitions. The number of repetitions in each case study was part of a sequential strategy for the direct study of repetitions and their likely influence on variation, which was affected by the chronological order in which the experiments were executed in this investigation. This chronological order (Fig. 6.1) also explains the decisions made in earlier case studies (Chapter 3) about dealing with the number of repetitions used. Therefore, setting the lower level should consider at least two repetitions since not performing repetitions may not be desirable because of the implicit probabilistic issues (Ross, 1988). However, there may be some associated problems when using two repetitions in combination with robust statistics, which skip extreme values (downsized and oversized) to make the sample robust (Hampel *et al*, 1986). On the other hand, if all case studies should be included the turning case study (Taher, 1995) sets the upper limit with four repetitions. Based on these considerations an initial setting choice was made with two and four repetitions for the investigation including all four case studies. Problems experienced earlier in this work (Chapter 3) with level selection (lacking enough spacing between them), which had an incidence on the final result, may be faced again with a selection of 2 (low) and 4 (high) repetitions. To avoid this an additional evaluation including a higher level of repetitions (eight) may be required at a later stage.

The statistics factor considered the use of robust estimators (Section 2.3.4) for location and dispersion (trimmed mean and Gini's mean, respectively) instead of normal estimators such as mean and standard deviation, even though it would not be expected that these would be necessary in any of the cases here. Each one of this pair (normal and robust) became a level for this factor.

The need for a design in which no information can be omitted combined with the fact that estimation of all possible interactions was also required pointed at a full factorial design. Therefore, once factors and levels were selected, they were fitted into a 2-level full factorial array featuring 2^4=16 runs, which were fully randomised. Exactly the same array (Table 6.5) was utilised for the four case studies maintaining identical randomised order. The randomisation process was done automatically through SAS (SAS Institute, 1991).

Factors	**Level 1**	**Level 2**
Method	Full Factorial	Taguchi
Repetitions	2	4
Transformations	None	Optimal
Statistics	Normal	Robust

Table 6.3 Tools study screening array with four two-level factors.

<table>
<tr><th colspan="2">Case Study</th><th># Repetitions</th></tr>
<tr><td colspan="2">Turning</td><td>4</td></tr>
<tr><td rowspan="3">Milling</td><td>1st block</td><td>8</td></tr>
<tr><td>2nd block</td><td>4</td></tr>
<tr><td>1st and 2nd block</td><td>4</td></tr>
<tr><td colspan="2">Traffic flow</td><td>8</td></tr>
<tr><td colspan="2">GA</td><td>8</td></tr>
</table>

Table 6.4 Number of repetitions under review per case study

Run	Method	Repetitions	Transformations	Statistics
1	Taguchi	2	Optimal	Robust
2	Taguchi	4	Optimal	Robust
3	FF	2	None	Normal
4	FF	4	Optimal	Normal
5	FF	2	Optimal	Normal
6	FF	2	None	Robust
7	Taguchi	4	None	Normal
8	FF	4	Optimal	Robust
9	FF	2	Optimal	Robust
10	Taguchi	4	None	Robust
11	Taguchi	2	Optimal	Normal
12	Taguchi	2	None	Robust
13	FF	4	None	Normal
14	Taguchi	4	Optimal	Normal
15	FF	4	None	Robust
16	Taguchi	2	None	Normal

Table 6.5 Special full factorial array for case study evaluation.

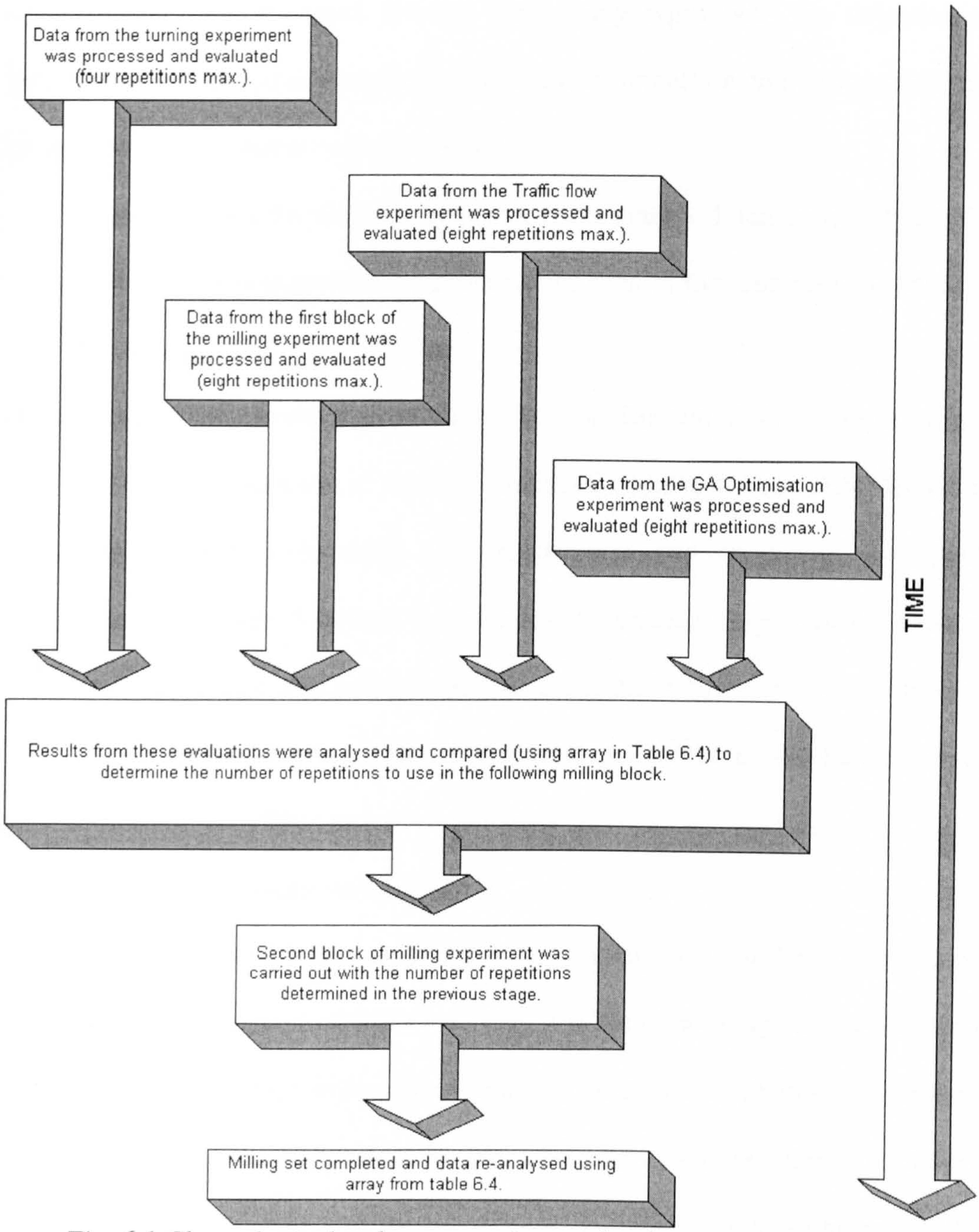


Fig. 6.1 Chronological order to experimentation for study of repetitions

6.3.2 Data acquisition phase

The special (full factorial) array (Table 6.5), with four tools under study (method, repetitions, transformations and statistics), was analysed using raw data from the case studies and relating them to location and dispersion metrics. The case studies were examined through these array types with the objective of determining the importance of these tools and their impact on controlling mean and dispersion. The procedure was as follows:

(i) The raw data for the case objective from Table 6.1 (eg surface finish for Milling investigation) were collected for each of the four cases (ie Milling, Turning, Traffic flow and GAs).

(ii) Each of the combinations in Table 6.5 (eg Taguchi array + 2 repetitions + No transformation + Robust statistics) selected raw data from (i) appropriately (for array and repetitions) and processed this (with transformations followed by statistics) to produce responses for location and dispersion with each of the four cases. Each of these sets of responses was averaged to give location and dispersion data for the full-factorial array of Table 6.5. These were then analysed

(iii) and dot-line graphs produced.

At this stage SNR was deliberately ignored since it had been proven unreliable in the previous case studies. Also, it is worth pointing out that the order in which the combination of factors is applied to the data on each run might make a difference. However, in deciding on this approach it was felt that a deliberate attempt should be made to approach the initial analysis as an engineer might, ignoring the need for a data transformation or any apparent link between mean and dispersion. These raw results were then compared with results of analysis following data transformation, where appropriate, to establish the relative importance of this action, and the dangers of accepting results without consideration of the nature of the patterns within the data.

The application of transformation in step (ii) deserves a special comment since it may be applied in two different ways: transforming the raw data and then calculate metrics or calculate metrics and transform the result. The former was favoured in this study since it represents data "as it is" resulting in a far more optimised procedure in terms of variation. Though the latter may put more pressure on the significance of the interaction between transformation and statistics factors, indicating an interesting aspect for further study, it may not be so accurate because if robust statistics are involved the transformation may ignore the discharged values. At the same time, it may be questioned whether it makes sense to transform the standard deviation.

6.3.3 Data analysis phase

Data analysis was carried out by applying the same statistical tools (such as ANOVA, factor/level analysis, correlation tests, etc.) that have been used in this investigation to determine factor significance. Only Pareto charts were dropped since no particular analyses (ie determining presence/absence of split-plot designs) were required. Analyses were carried out on the data sets obtained after processing raw data from the individual case studies through the special array (Tables 6.6 to 6.9). ANOVA results (Tables 6.10 to 6.13) suggested that transformation emerged as by far the most significant factor for both location and dispersion in all case studies. The very high F-Value for Transformations (Tables 6.10 to 6.13) reduces the remaining factors to very secondary roles. Method and repetitions alternated the second and third significant largest effects in most cases (except in milling first block) after transformations on both location and dispersion. The milling data set suggested statistics as the second largest effect after transformations. However, for the kinds of data for all these cases there should be no need to use robust indicators and, therefore, as expected, this factor was not significant (Tables 6.10, 6.12 and 6.13) and had no effect on outcomes. Finally, and of most interest, half of the cases favoured the significance of method factor (Tables 6.10 and 6.11). However, if seen from the other perspective, the fact that the other half was not significant or had negligible effect on outcome may be a positive result for Taguchi as it suggests that full factorial designs performed only marginally better than Taguchi designs (in those cases). This is despite the evidence on the significance of interactions for all cases in this study. At this stage, this should be regarded with caution and requiring additional evaluation for assessing its significance prior to making any further judgement. On the other hand, there were some significant interactions involving method with both transformations and repetitions, interactions that may be influenced by the importance of the other factors. In addition, interaction between repetitions and transformations was found consistently significant in most cases.

Charts are often used to determine important interactions in Taguchi as well as full factorial designs, providing a visually effective tool for most engineers. In this respect, main factor dot-line plots indicated that the difference between using optimal transformations (Box-Cox method) (Fig. 6.2) and not using transformations at all proved to be substantial, with a clear positive inclination for optimal (a power transformation of the response) on both location (Fig. 6.3) and dispersion (Fig. 6.4). The effect of this factor proved so high, indicated by F-values (Tables 6.10 to 6.13), that it certainly had a detrimental effect on other factors to the point that they appear to be unimportant in these dot-line plots.

Despite this situation affecting the process of determining optimal levels for each factor (dot-lines with gradient near zero), it was possible to (roughly) estimate best settings from these plots. Optimal transformations, four repetitions, normal statistics and full factorial arrays were the best settings for both location and dispersion. Though choosing the best level for the method factor was hard, the decision of going for full factorial arrays was suggested by results obtained from the GA optimisation data sets. Significant second-order interactions have been detected in all these case studies. Dot-line plots for location (Figs. 6.5 to 6.8) and dispersion (Figs. 6.9 to 6.12) did not show clear indications of significant interaction since most lines were overlapping, making it difficult to appreciate their gradients. This may also be a consequence of the transformation factor weighting for most of the effects, affecting the plotting scale.

					Raw data		**Transformed data**	
Run	**Method**	**Repetitions**	**Transformations**	**Statistics**	**Location**	**Dispersion**	**Location**	**Dispersion**
1	Taguchi	2	Optimal	Robust	4.341667	1.457763	1.368738	0.357644
2	Taguchi	4	Optimal	Robust	4.416667	1.270132	1.436308	0.28949
3	FF	2	None	Normal	4.412033	1.403025		
4	FF	4	Optimal	Normal	4.434514	1.278458	1.420421	0.29227
5	FF	2	Optimal	Normal	4.412033	1.403025	1.4151	0.3212
6	FF	2	None	Robust	4.4122	1.4003		
7	Taguchi	4	None	Normal	4.48287	1.221463		
8	FF	4	Optimal	Robust	4.3456	1.3062	1.4193	0.3012
9	FF	2	Optimal	Robust	4.4122	1.4003	1.4149	0.3209
10	Taguchi	4	None	Robust	4.416667	1.270132		
11	Taguchi	2	Optimal	Normal	4.341667	1.457763	1.368738	0.357644
12	Taguchi	2	None	Robust	4.341667	1.457763		
13	FF	4	None	Normal	4.434514	1.278458		
14	Taguchi	4	Optimal	Normal	4.48287	1.221463	1.422997	0.286568
15	FF	4	None	Robust	4.3456	1.3062		
16	Taguchi	2	None	Normal	4.341667	1.457763		

Table 6.6 Turning case study evaluation data set.

					Raw data		Transformed data	
Run	**Method**	**Repetitions**	**Transformations**	**Statistics**	**Location**	**Dispersion**	**Location**	**Dispersion**
1	Taguchi	2	Optimal	Robust	2.459	2.794	0.782	0.383
2	Taguchi	4	Optimal	Robust	2.496	2.915	0.823	0.402
3	FF	2	None	Normal	3.228	6.594		
4	FF	4	Optimal	Normal	3.160	6.388	0.819	0.373
5	FF	2	Optimal	Normal	3.228	6.594	0.813	0.370
6	FF	2	None	Robust	2.623	3.070		
7	Taguchi	4	None	Normal	3.442	7.716		
8	FF	4	Optimal	Robust	2.525	2.881	0.838	0.385
9	FF	2	Optimal	Robust	2.623	3.070	0.832	0.381
10	Taguchi	4	None	Robust	2.496	2.915		
11	Taguchi	2	Optimal	Normal	3.368	7.436	0.758	0.368
12	Taguchi	2	None	Robust	2.459	2.794		
13	FF	4	None	Normal	3.160	6.388		
14	Taguchi	4	Optimal	Normal	3.442	7.716	0.797	0.387
15	FF	4	None	Robust	2.525	2.881		
16	Taguchi	2	None	Normal	3.368	7.436		

Table 6.7 Milling (1st block) case study evaluation data set.

					Raw data		Transformed data	
Run	**Method**	**Repetitions**	**Transformations**	**Statistics**	**Location**	**Dispersion**	**Location**	**Dispersion**
1	Taguchi	2	Optimal	Robust	20.802	11.445	1.230	0.041
2	Taguchi	4	Optimal	Robust	20.611	11.102	1.229	0.040
3	FF	2	None	Normal	19.803	10.121		
4	FF	4	Optimal	Normal	19.770	9.974	1.227	0.036
5	FF	2	Optimal	Normal	19.803	10.121	1.227	0.038
6	FF	2	None	Robust	19.504	9.608		
7	Taguchi	4	None	Normal	20.373	11.214		
8	FF	4	Optimal	Robust	19.467	9.551	1.227	0.038
9	FF	2	Optimal	Robust	19.504	9.608	1.227	0.038
10	Taguchi	4	None	Robust	20.611	11.102		
11	Taguchi	2	Optimal	Normal	20.558	11.589	1.229	0.038
12	Taguchi	2	None	Robust	20.802	11.445		
13	FF	4	None	Normal	19.770	9.974		
14	Taguchi	4	Optimal	Normal	20.373	11.214	1.228	0.037
15	FF	4	None	Robust	19.467	9.551		
16	Taguchi	2	None	Normal	20.558	11.589		

Table 6.8 Traffic flow case study evaluation data set.

					Raw data		Transformed data	
Run	**Method**	**Repetitions**	**Transformations**	**Statistics**	**Location**	**Dispersion**	**Location**	**Dispersion**
1	Taguchi	2	Optimal	Robust	22553.647	21312.330	0.120	0.032
2	Taguchi	4	Optimal	Robust	20655.920	21060.288	0.123	0.032
3	FF	2	None	Normal	20090.498	16173.523		
4	FF	4	Optimal	Normal	17980.515	13424.242	0.354	0.031
5	FF	2	Optimal	Normal	20090.498	16173.523	0.350	0.034
6	FF	2	None	Robust	20396.061	20020.062		
7	Taguchi	4	None	Normal	21016.954	14032.059		
8	FF	4	Optimal	Robust	18305.127	18198.576	0.353	0.045
9	FF	2	Optimal	Robust	20396.061	20020.062	0.349	0.046
10	Taguchi	4	None	Robust	20655.920	21060.288		
11	Taguchi	2	Optimal	Normal	23396.579	16940.979	0.186	0.108
12	Taguchi	2	None	Robust	22553.647	21312.330		
13	FF	4	None	Normal	17980.515	13424.242		
14	Taguchi	4	Optimal	Normal	21016.954	14032.059	0.189	0.109
15	FF	4	None	Robust	18305.127	18198.576		
16	Taguchi	2	None	Normal	23396.579	16940.979		

Table 6.9 GA Optimisation case study evaluation data set.

		DF	**Seq SS**	**Adj SS**	**Adj MS**	**F Value**	**P>F**
Location	**Method**	1	0.001	0.001	0.001	0.860	0.395
	Repetitions	1	0.006	0.006	0.006	8.930	0.030
	Transformations	1	35.763	35.763	35.763	55000.0	0.000
	Statistics	1	0.001	0.001	0.001	1.980	0.218
	Method*Repetitions	1	0.009	0.009	0.009	13.440	0.015
	Method*Transf.	1	0.000	0.000	0.000	0.260	0.634
	Method*Statistics	1	0.000	0.000	0.000	0.130	0.729
	Repetiti*Transf.	1	0.000	0.000	0.000	0.160	0.706
	Repetiti*Statistics	1	0.001	0.001	0.001	1.980	0.219
	Transf.*Statistics	1	0.002	0.002	0.002	2.700	0.161
	Error	5	0.003	0.003	0.001		
	Total	15	35.785				
Dispersion	**Method**	1	0.000	0.000	0.000	1.460	0.281
	Repetitions	1	0.043	0.043	0.043	179.240	0.000
	Transformations	1	4.273	4.273	4.273	18000.0	0.000
	Statistics	1	0.000	0.000	0.000	1.890	0.228
	Method*Repetitions	1	0.005	0.005	0.005	22.750	0.005
	Method*Transf.	1	0.000	0.000	0.000	0.350	0.580
	Method*Statistics	1	0.000	0.000	0.000	0.080	0.784
	Repetiti*Transf.	1	0.013	0.013	0.013	53.740	0.001
	Repetiti*Statistics	1	0.001	0.001	0.001	2.170	0.201
	Transf.*Statistics	1	0.000	0.000	0.000	1.000	0.362
	Error	5	0.001	0.001	0.000		
	Total	15	4.337				

Table 6.10 ANOVA test for location and dispersion (on Table 6.6) study for significance of statistical tools (turning case study).

		DF	Seq SS	Adj SS	Adj MS	F Value	P>F
Location	Method	1	0.001	0.001	0.001	0.090	0.781
	Repetitions	1	0.000	0.000	0.000	0.020	0.906
	Transformations	1	17.722	17.722	17.722	3209.95	0.000
	Statistics	1	0.565	0.565	0.565	102.360	0.000
	Method*Repetitions	1	0.007	0.007	0.007	1.350	0.298
	Method*Transf.	1	0.009	0.009	0.009	1.560	0.267
	Method*Statistics	1	0.023	0.023	0.023	4.120	0.098
	Repetiti*Transf.	1	0.001	0.001	0.001	0.240	0.642
	Repetiti*Statistics	1	0.000	0.000	0.000	0.050	0.836
	Transf.*Statistics	1	0.633	0.633	0.633	114.690	0.000
	Error	5	0.028	0.028	0.006		
	Total	15	18.989				
Dispersion	Method	1	0.240	0.240	0.240	2.940	0.147
	Repetitions	1	0.000	0.000	0.000	0.000	0.966
	Transformations	1	84.387	84.387	84.387	1035.55	0.000
	Statistics	1	16.853	16.853	16.853	206.810	0.000
	Method*Repetitions	1	0.043	0.043	0.043	0.520	0.501
	Method*Transf.	1	0.225	0.225	0.225	2.760	0.158
	Method*Statistics	1	0.362	0.362	0.362	4.440	0.089
	Repetiti*Transf.	1	0.000	0.000	0.000	0.000	0.974
	Repetiti*Statistics	1	0.001	0.001	0.001	0.020	0.907
	Transf.*Statistics	1	17.071	17.071	17.071	209.490	0.000
	Error	5	0.407	0.407	0.081		
	Total	15	119.590				

Table 6.11 ANOVA test for location and dispersion (on Table 6.7) study for significance of statistical tools (milling case study).

		DF	Seq SS	Adj SS	Adj MS	F Value	P>F
Location	Method	1	0.910	0.910	0.910	57.400	0.001
	Repetitions	1	0.010	0.010	0.010	0.790	0.414
	Transformations	1	1426.27	1426.27	1426.27	90000.0	0.000
	Statistics	1	0.000	0.000	0.000	0.060	0.824
	Method*Repetitions	1	0.010	0.010	0.010	0.380	0.567
	Method*Transf.	1	0.900	0.900	0.900	56.910	0.001
	Method*Statistics	1	0.070	0.070	0.070	4.670	0.083
	Repetiti*Transf.	1	0.010	0.010	0.010	0.780	0.417
	Repetiti*Statistics	1	0.000	0.000	0.000	0.000	0.985
	Transf.*Statistics	1	0.000	0.000	0.000	0.060	0.818
	Error	5	0.080	0.080	0.020		
	Total	15	1428.26				
Dispersion	Method	1	2.327	2.327	2.327	250.800	0.000
	Repetitions	1	0.054	0.054	0.054	5.780	0.061
	Transformations	1	444.135	444.135	444.135	48000.0	0.000
	Statistics	1	0.088	0.088	0.088	9.440	0.028
	Method*Repetitions	1	0.017	0.017	0.017	1.780	0.240
	Method*Transf.	1	2.318	2.318	2.318	249.820	0.000
	Method*Statistics	1	0.029	0.029	0.029	3.150	0.136
	Repetiti*Transf.	1	0.053	0.053	0.053	5.680	0.063
	Repetiti*Statistics	1	0.001	0.001	0.001	0.100	0.761
	Transf.*Statistics	1	0.090	0.090	0.090	9.700	0.026
	Error	5	0.046	0.046	0.009		
	Total	15	449.157				

Table 6.12 ANOVA test for location and dispersion (on Table 6.8) study for significance of statistical tools (traffic flow case study).

		DF	Seq SS	Adj SS	Adj MS	F Value	P>F
Location	Method	1	7357807	7357807	7357807	145.380	0.000
	Repetitions	1	4492550	4492550	4492550	88.770	0.000
	Transformations	1	1689071845	1689071845	1689071845	33000.00	0.000
	Statistics	1	20587	20587	20587	0.410	0.552
	Method*Repetitions	1	365.000	365.000	365.000	0.010	0.936
	Method*Transf.	1	7359944	7359944	7359944	145.420	0.000
	Method*Statistics	1	210284	210284	210284	4.150	0.097
	Repetiti*Transf.	1	4492580	4492580	4492580	88.770	0.000
	Repetiti*Statistics	1	15684	15684	15684	0.310	0.602
	Transf.*Statistics	1	20568	20568	20568	0.410	0.552
	Error	5	253053	253053	50611		
	Total	15	1713295268				
Dispersion	Method	1	1910876	1910876	1910876	5.36	0.069
	Repetitions	1	3736230	3736230	3736230	10.47	0.023
	Transformations	1	1245412720	1245412720	1245412720	3491.11	0
	Statistics	1	25050841	25050841	25050841	70.22	0
	Method*Repetitions	1	124223	124223	124223	0.35	0.581
	Method*Transf.	1	1910704	1910704	1910704	5.36	0.069
	Method*Statistics	1	482514	482514	482514	1.35	0.297
	Repetiti*Transf.	1	3736224	3736224	3736224	10.47	0.023
	Repetiti*Statistics	1	803118	803118	803118	2.25	0.194
	Transf.*Statistics	1	25051476	25051476	25051476	70.22	0
	Error	5	1783692	1783692	356738		
	Total	15	1310002618				

Table 6.13 ANOVA test for location and dispersion (on Table 6.9) study for significance of statistical tools (GA optimisation case study).

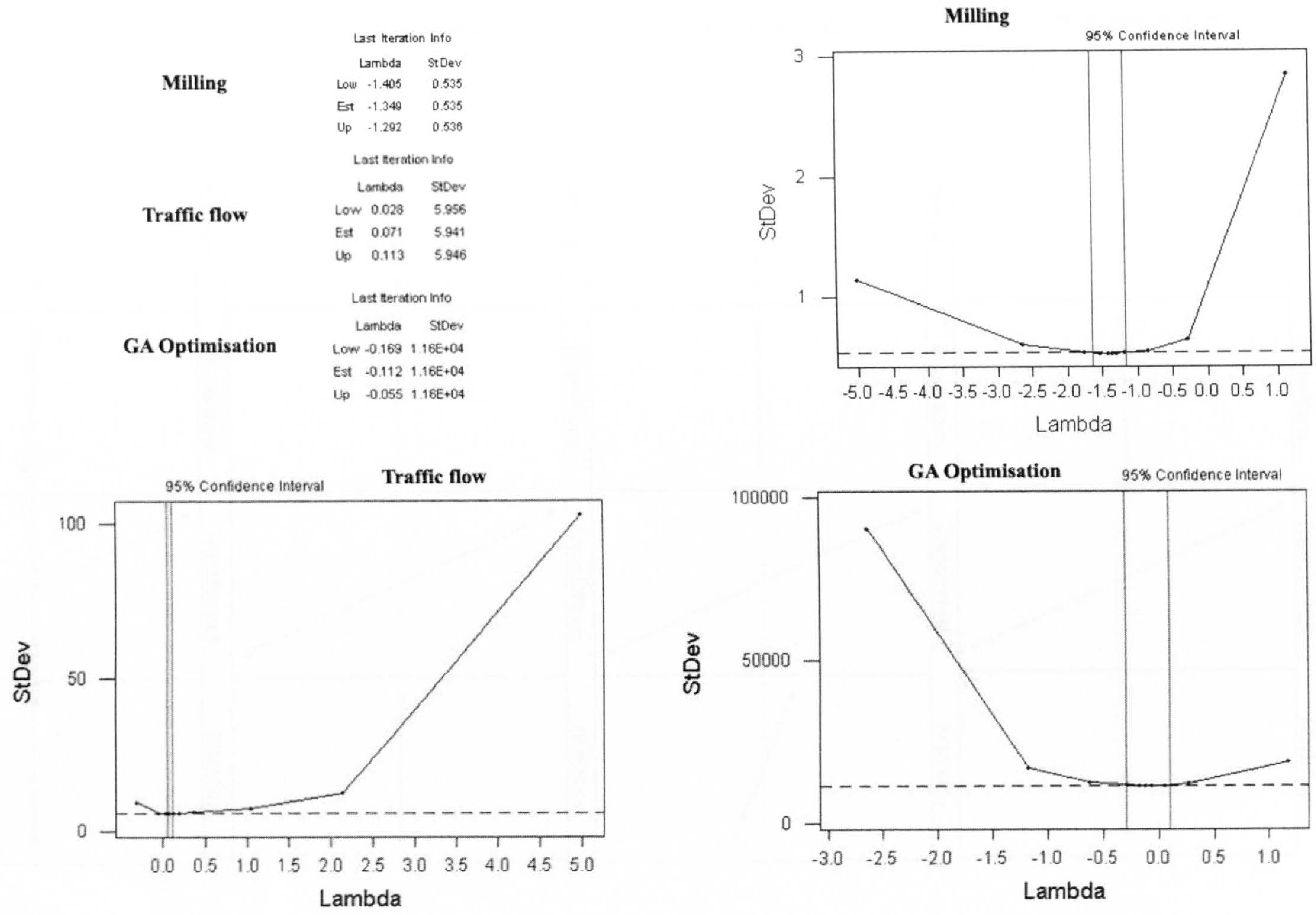


Fig. 6.2 Plots for determining the optimal transformation with the Box-Cox method (N.B. for turning optimal transformation see Taher, 1995)

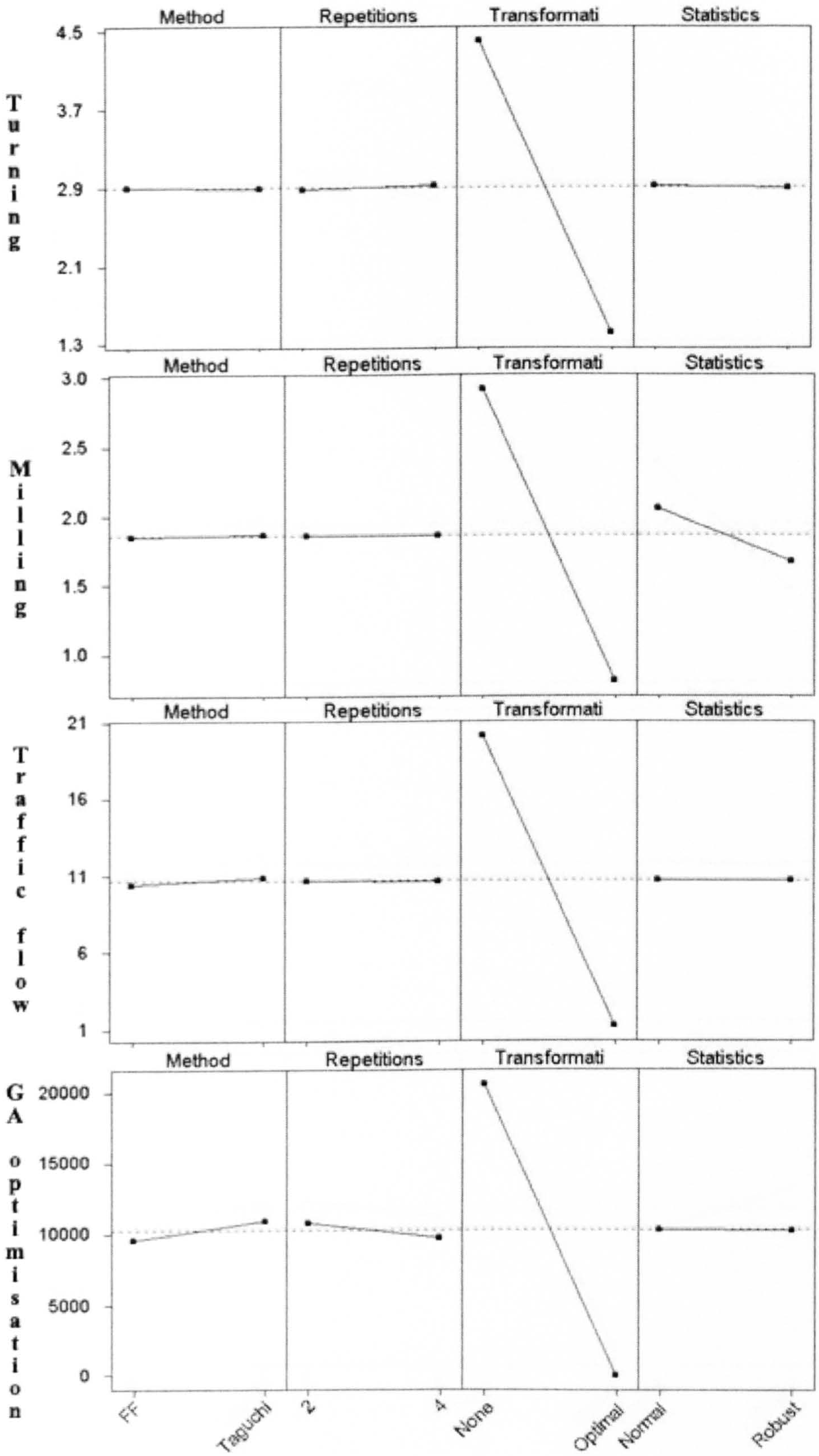


Fig. 6.3 Dot-line plots for main factors – Location (all case studies).

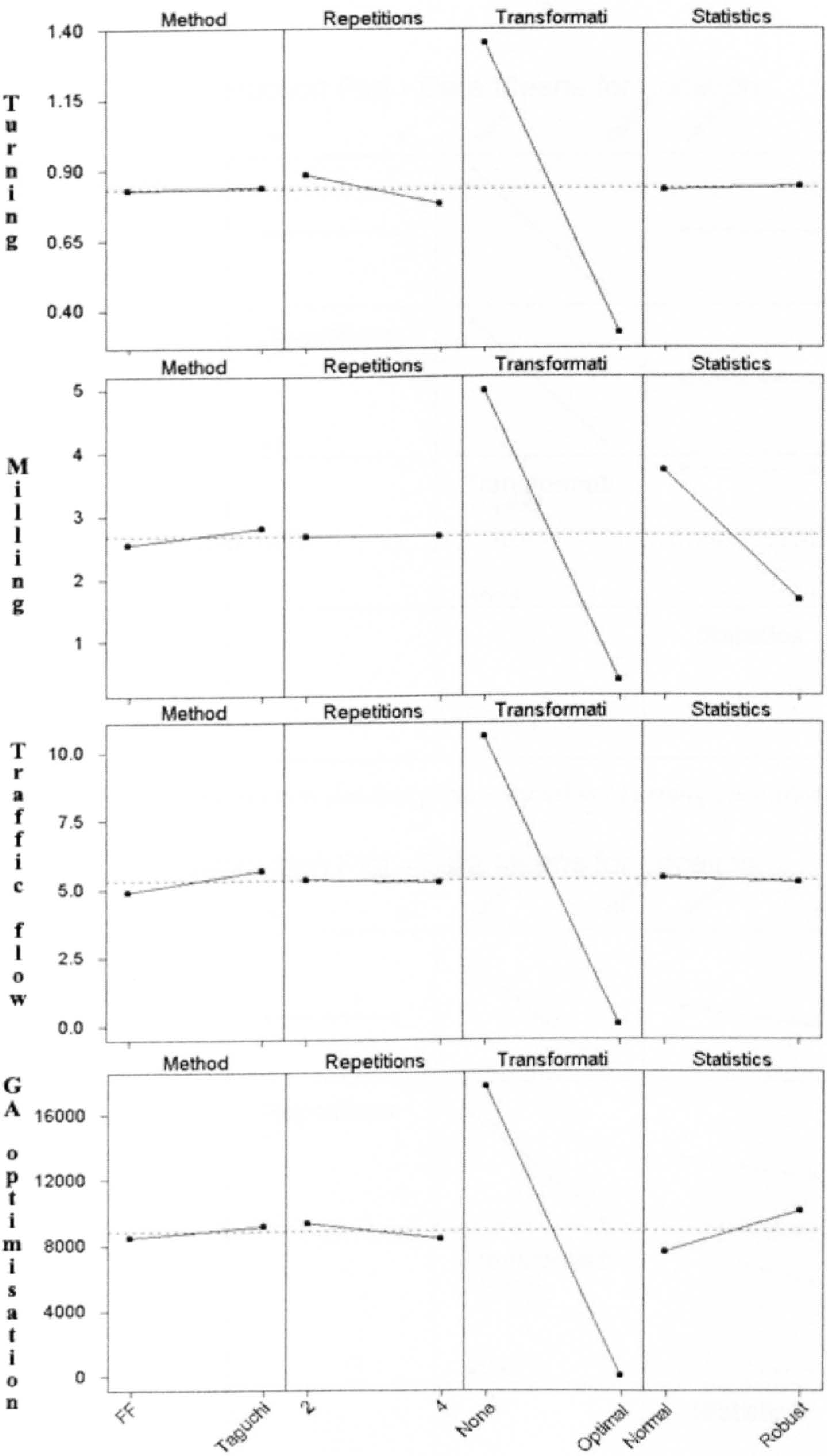


Fig. 6.4 Dot-line plots for main factors – Dispersion (all case studies).

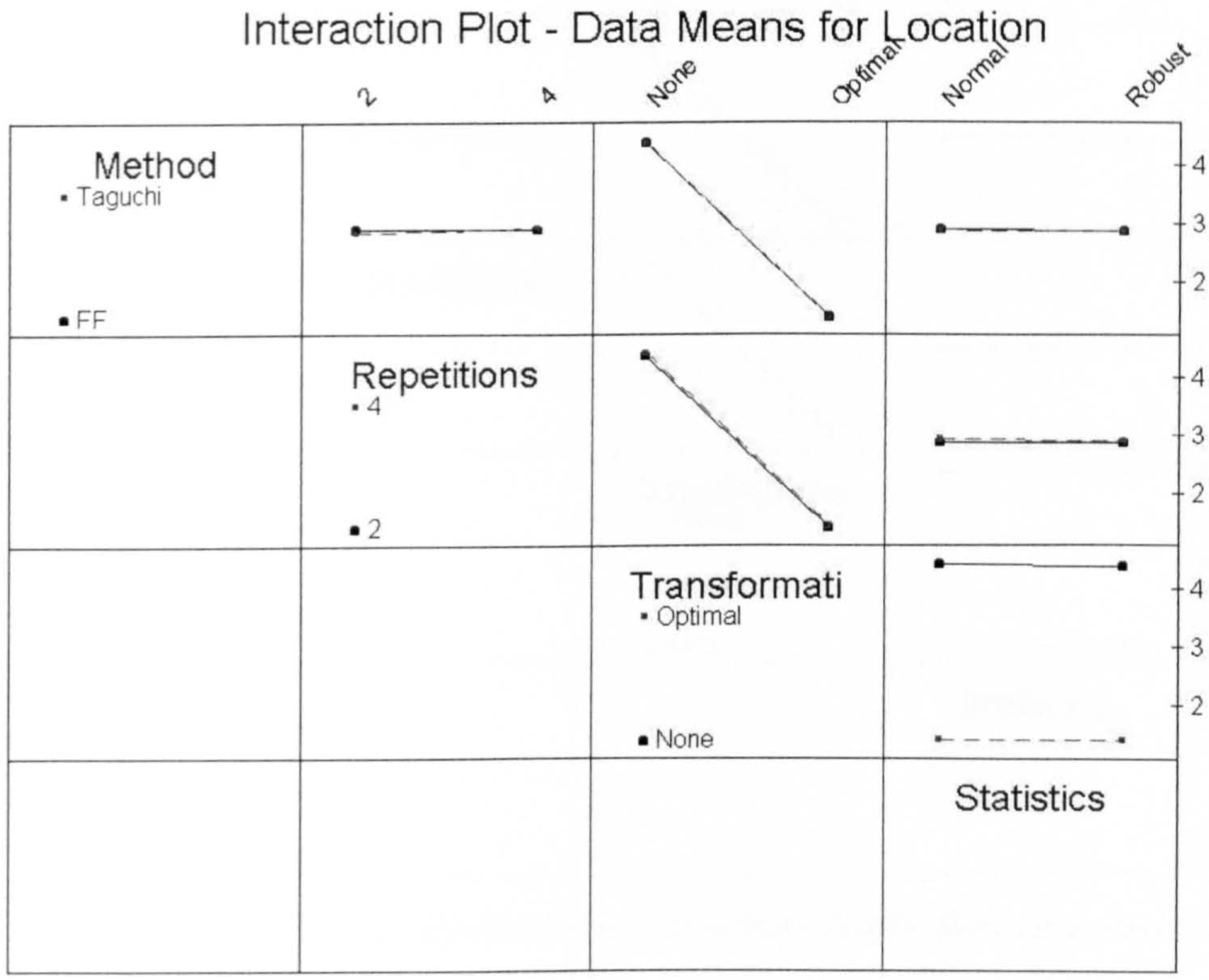


Fig. 6.5 Interaction dot-line plots – location (Turning case study).

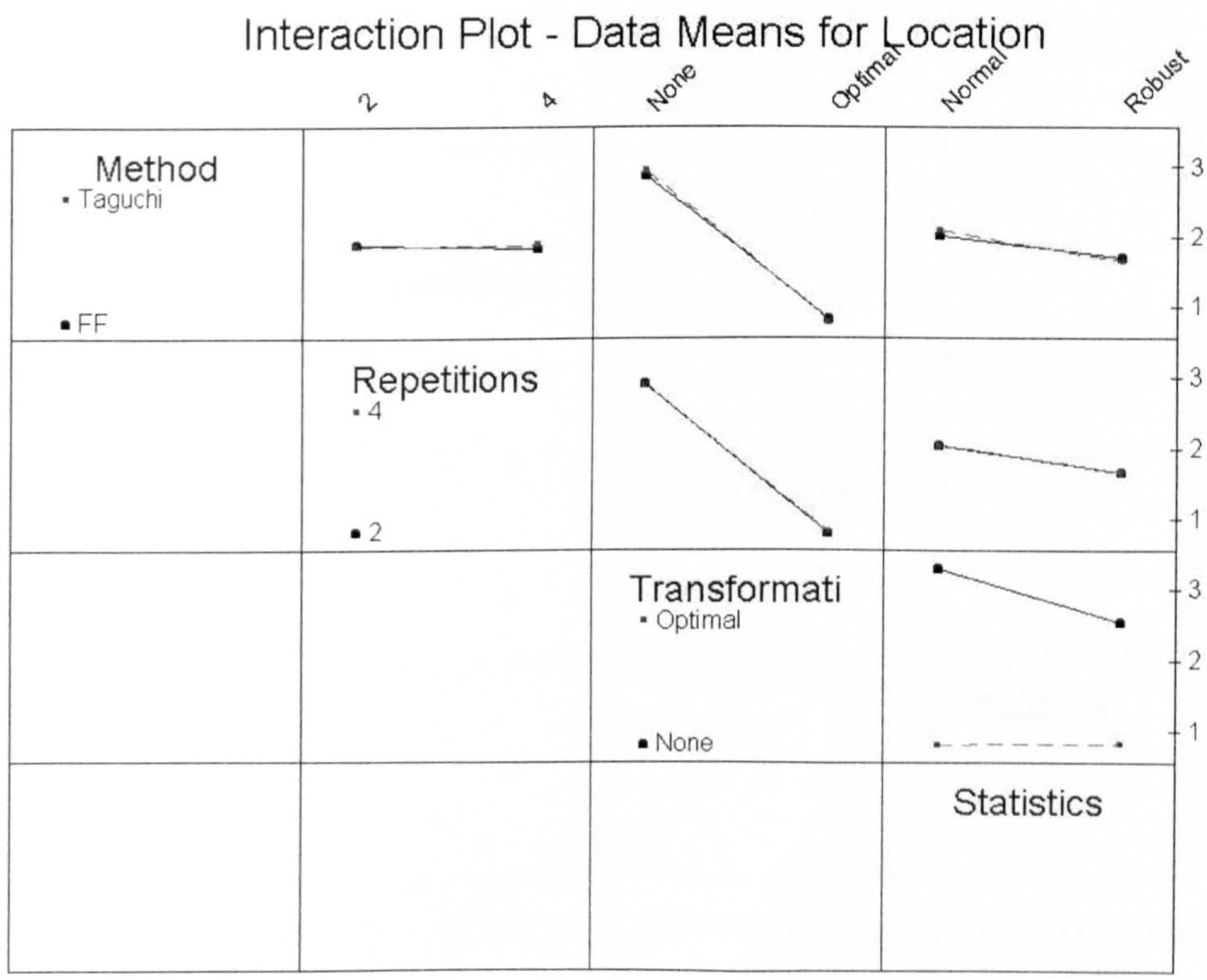


Fig. 6.6 Interaction dot-line plots – location (Milling case study).

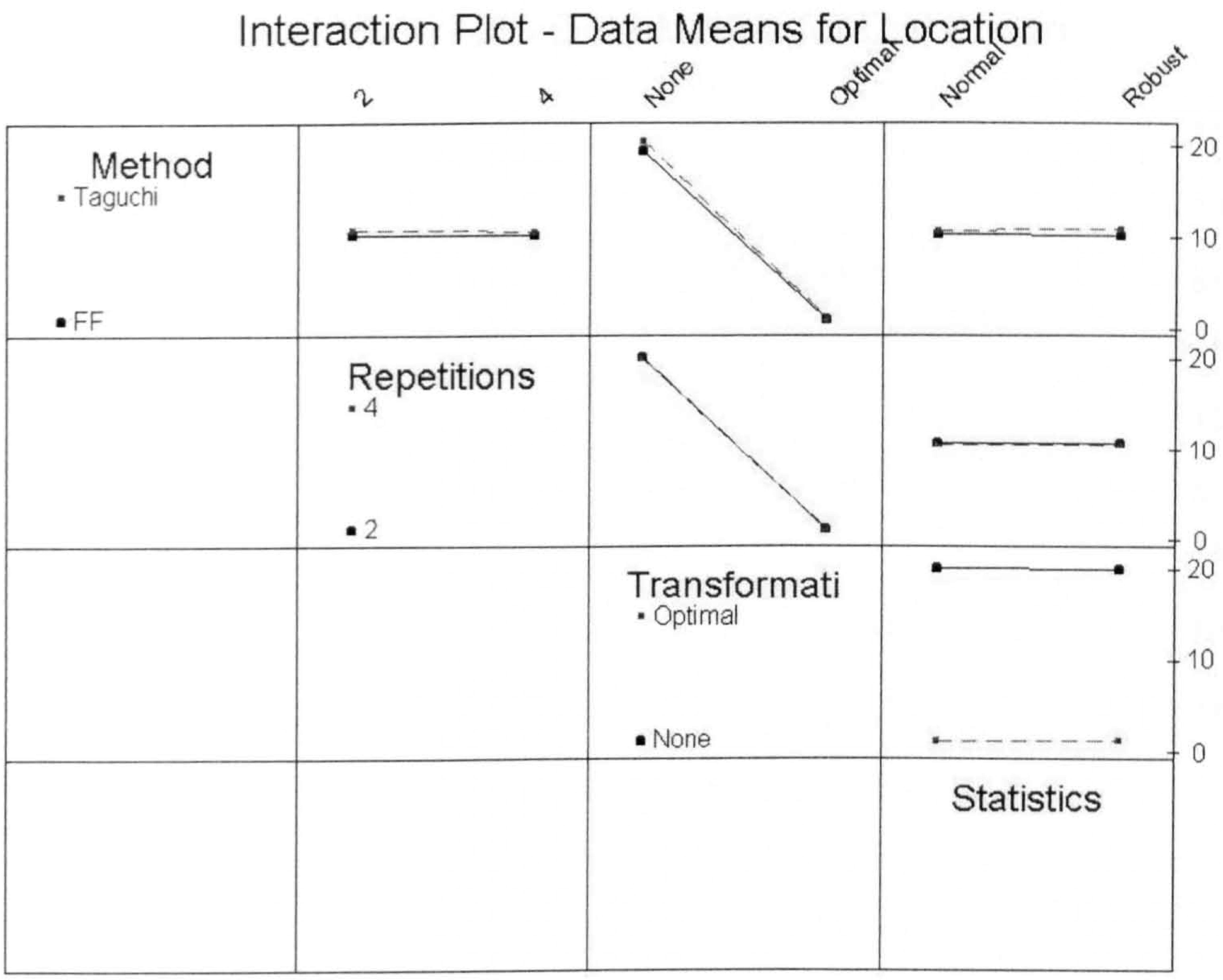


Fig. 6.7 Interaction dot-line plots – location (Traffic flow case study).

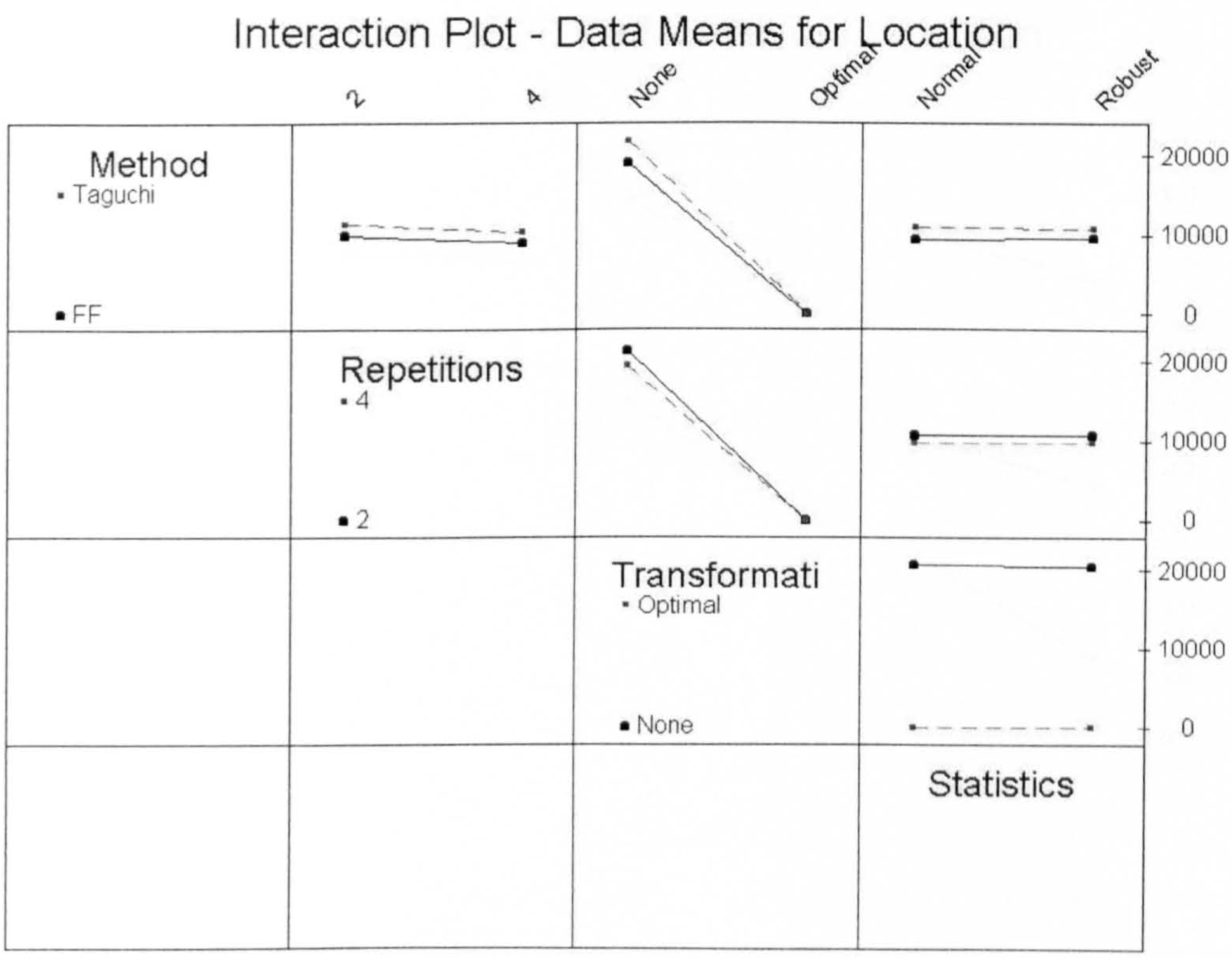


Fig. 6.8 Interaction dot-line plots – location (GA Optimisation case study).

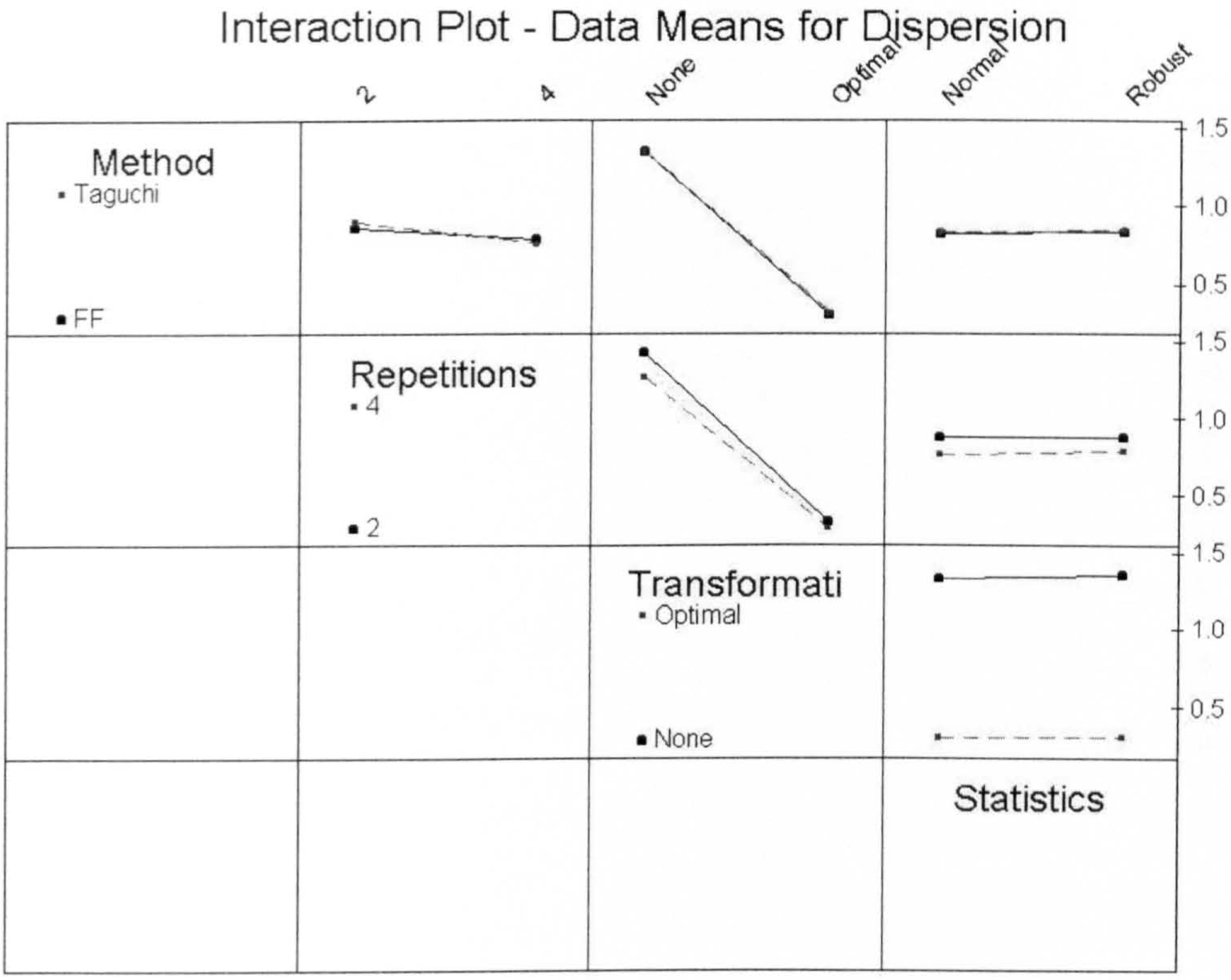


Fig. 6.9 Interaction dot-line plots – Dispersion (Turning case study).

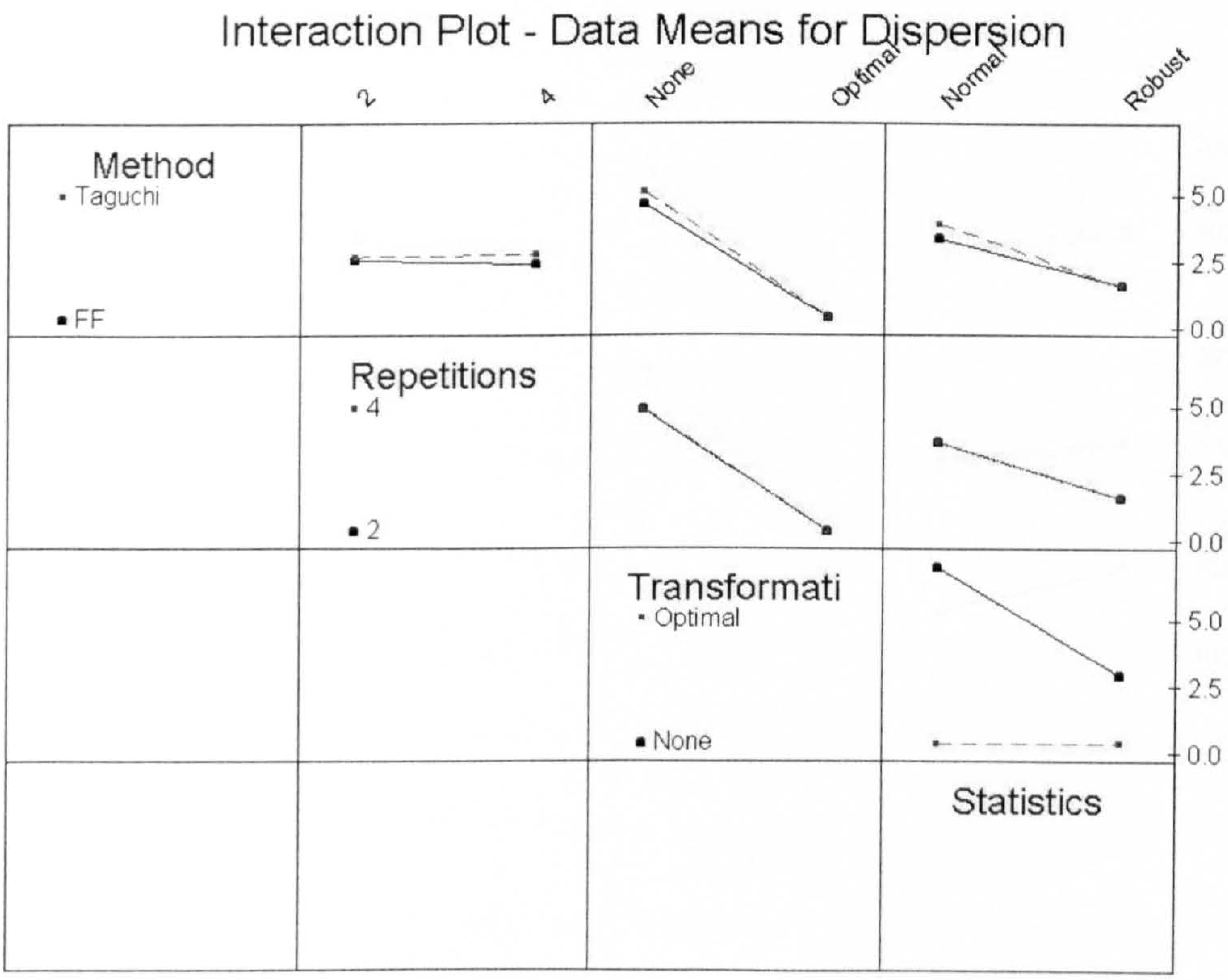


Fig. 6.10 Interaction dot-line plots – Dispersion (Milling case study).

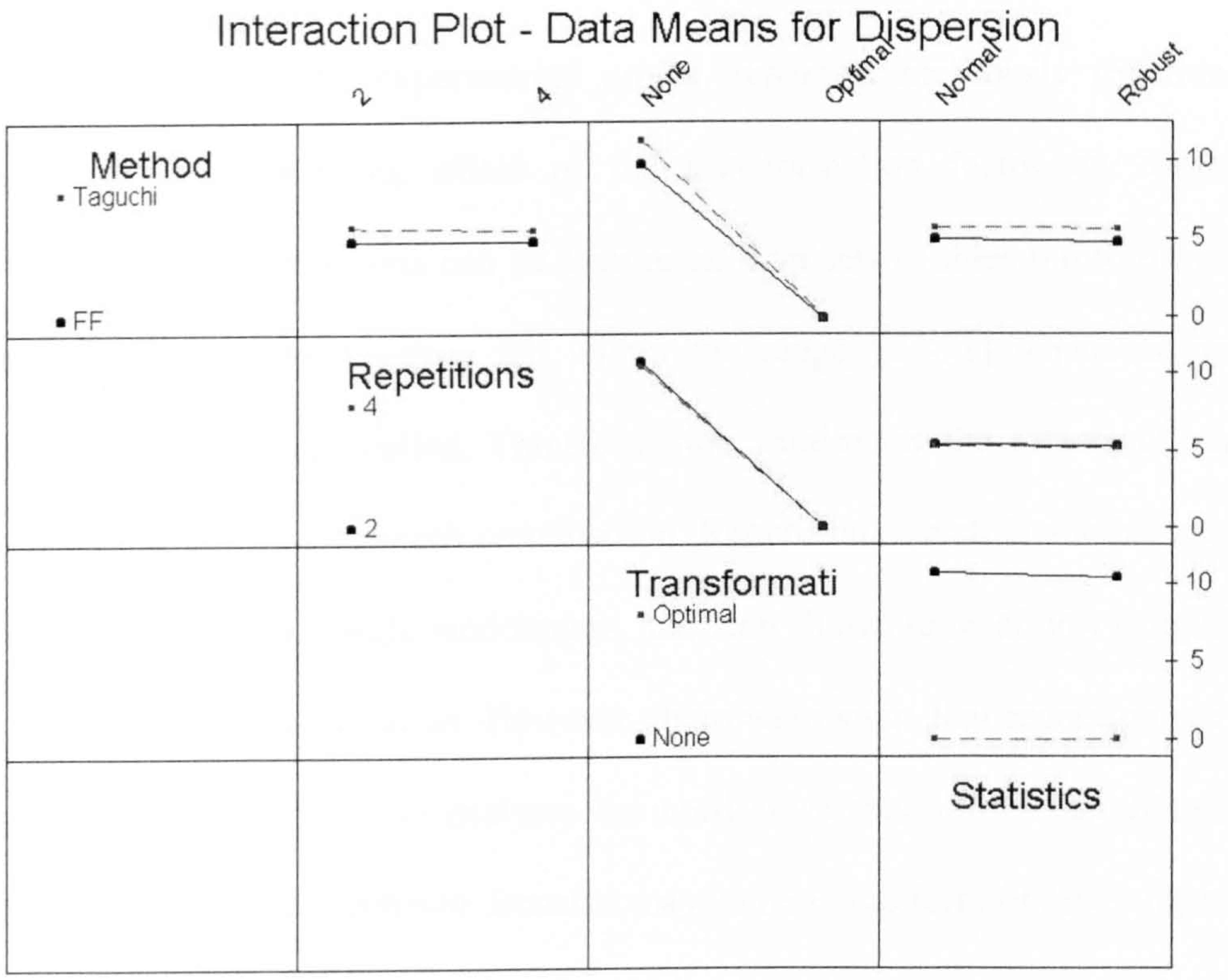


Fig. 6.11 Interaction dot-line plots – Dispersion (Traffic flow case study).

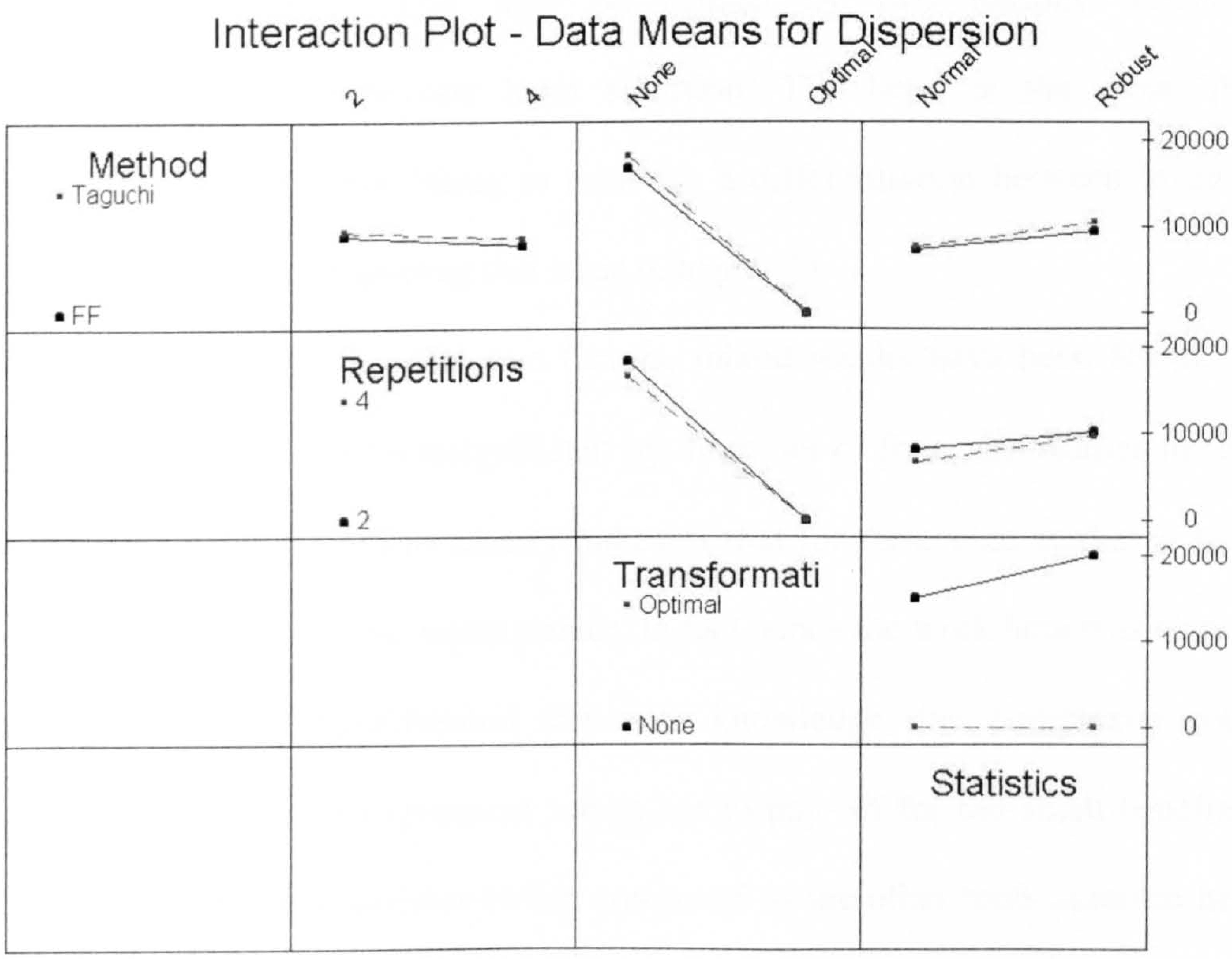


Fig. 6.12 Interaction dot-line plots – Dispersion (GA Optimisation case study).

6.4 Discussion

Results for the experimental arrays evaluated previously (Section 6.3) indicated the outstanding effect of the transformation factor on controlling dispersion. Evidence of this can be seen in all data sets (Tables 6.6 to 6.9) where transformed dispersion values fell within the range [0 - 1] whenever optimal transformations were applied. Transformation minimises the effects of random variations in the data for each combination. Repetition, which is another resource commonly believed to fight randomness, has been shown to be almost insignificant if compared to transformation. However, there were signs that repetition may still be beneficial if factor/level analyses are used since this allows identification of appropriate levels of repetition. Benefits may come in the form of fewer repetitions without affecting reliability though results found at this stage may not be considered conclusive. This may be caused by two reasons: effect of transformations and repetition level selection. The latter is the most likely explanation of repetitions failing to establish a differentiation between levels, as there was a precedent regarding this issue (Chapter 3).

In relation to the other two factors, mixed results have been found. The statistics factor was shown insignificant by three out of four case studies for both location and dispersion. This clearly indicates that for these case studies it seems not to offer benefits for the experimenter. In fact, since the work here was aimed at experimenters with basic/limited statistical knowledge, the complexity robust statistics bring into the experiment seems not to pay off for the small benefits in dispersion reduction it delivers (when compared to the other tools assessed here). On the other hand, it did prove to have a positive effect on the milling case study, where it was found significant, though this may have been caused by the special characteristics of the data, which fit the type of problems robust statistics are made for. The presence of extreme outliers within the milling data allowed this tool to perform well in these circumstances. Interaction dot-line plots (Fig. 6.10) suggested that robust methods were better for large data sets (such as full factorial arrays) and in cases where transformations were not applied. Otherwise, the use of transformations may do the job with normal estimators.

A similar situation was found with the method factor, with some of the case studies pointing at its lack of significance. A careful analysis of the interaction dot-line plots for the GA optimisation case study (Fig. 6.12), gave additional information (to ANOVA and main effect dot-line plots) of being significant (with full factorial as the best setting). This plot suggested that, despite the fact that full factorial performed slightly better for dispersion reduction, application of optimal transformations eliminated this difference. This, together with finding the method factor non-significant for some case studies, are very positive for Taguchi arrays since either way keeps them close in performance to full factorial arrays with the additional advantage of doing so with less runs. Comparable performance for both full factorial designs and Taguchi arrays on significant factor determination may simply indicate the appropriateness of Taguchi arrays as well as being another demonstration of their underestimated power.

A retrospective look at the previous analyses suggested further evaluation. Issues surrounding the method and repetition factors were the likely candidates for this investigation, which was done through the preparation of another designed experiment. Therefore, based on these outcomes, a new design (Table 6.14) studied only two factors (statistics factor screened out) at three levels each and the method factor at two levels trying to establish extra differentiation in the use of Taguchi designs and full factorial designs. Similarly, the effect of using optimal or non-optimal transformations on dispersion control was also studied (non-optimal transformation choice was a commonly used type, such as the Log family which may be optimal but not in these cases). The inclusion of non-optimal transformations was aimed at testing the implications of not using the appropriate transformation for the data in question. The repetition factor sought to determine whether more than the representative limit of four might deliver better information on dispersion, but therefore involved only those three case studies with eight repetitions available (milling machining, traffic signal control and simple genetic algorithms). The aim here was to explore the implications of the misapplication of these tools. The procedure followed was similar to that for the original screening array with the use of a mixture design (Table 6.15) this time.

The evaluation of the three data sets utilised in this phase (Tables 6.16 to 6.18) suggested, again, that transformation was the most important factor in all cases and for both location and dispersion (Tables 6.19 to 6.21). In fact, ANOVA results suggested that the three factors were significant for both location and dispersion, with the exception of repetitions which seemed unimportant in the traffic flow case study. Once again the effect of transformation is very high affecting the plotting scale and making the other two factors look unimportant. Using another tool such as Least Squares means, there was a clear difference in both location and dispersion control when optimal transformations (Fig. 6.15) were applied (Tables 6.22 to 6.24; Figs. 6.13 and 6.14) and a substantial difference between using optimal and non-optimal transformations (Figs. 6.13 and 6.14).

The method factor is now significant, indicating somewhat better performance (regarding both location and dispersion control) for full factorial designs in some cases. On the other hand, Taguchi arrays were a better choice for the milling (location and dispersion) and GA optimisation (location) case studies. Unfortunately, these results confirmed the findings of the previous phase, which were not conclusive though suggesting that Taguchi is still reliable for dispersion reduction. Finally, repetitions remain significant (Tables 6.19 to 6.21) but with only a small improvement on levels above two (Figs. 6.13 and 6.14). Looking at the main factor dot-line plots (Figs. 6.13 and 6.14) and Least Squares means (Tables 6.22 to 6.24) it can be seen that (as expected) the more repetitions the better. However, the gap between four and eight repetitions seems not as big as might be expected, indicating that four repetitions may be enough for industrial applications.

Regarding interactions, only the one between method and transformations has been pointed out by ANOVA in all three case studies for both location and dispersion. Additionally, the interaction between repetitions and transformation was also found significant for the GA optimisation and milling case studies. Looking at the dot-line plots (Figs. 6.16 to 6.21) about these interactions implied by ANOVA, the combination of Taguchi methods and optimal transformations seems to match the full factorial arrays without transformations. Also, regarding repetitions, those suggestions supporting the use of four repetitions have been found significant if seen from the interaction viewpoint. Dot-line plots (Figs. 6.19 to 6.21) indicated similar dispersion patterns when optimal transformations were used combined with either four or eight repetitions. Therefore, findings from this phase hinted that the use of Taguchi arrays with the help of optimal transformations and a "moderate" number (four in this case) of repetitions may yield a matching, or better, performance than full factorial designs.

Factors	Level 1	Level 2	Level 3
Replications	2	4	8
Transformations	None	Non optimal	Optimal
Method	Full Factorial	Taguchi	

Table 6.14 Second phase tools study mixture design ($2 \bullet 3^2$) with three factors.

Run	Method	Repetitions	Transformations
1	Taguchi	2	None
2	Taguchi	4	None
3	Taguchi	4	Optimal
4	FF	4	None
5	Taguchi	8	Optimal
6	FF	8	Non-optimal
7	Taguchi	2	Non-optimal
8	FF	8	None
9	FF	2	Non-optimal
10	FF	2	Optimal
11	FF	2	None
12	FF	4	Optimal
13	Taguchi	4	Non-optimal
14	FF	4	Non-optimal
15	Taguchi	8	None
16	Taguchi	2	Optimal
17	FF	8	Optimal
18	Taguchi	8	Non-optimal

Table 6.15 Second phase full factorial array for case study evaluation.

Run	Method	Repetitions	Transformations	Raw data Location	Raw data Dispersion	Transformed data Location	Transformed data Dispersion
1	Taguchi	2	None	3.368	7.436		
2	Taguchi	4	None	3.442	7.716		
3	Taguchi	4	Optimal	3.442	7.716	0.797	0.387
4	FF	4	None	3.160	6.388		
5	Taguchi	8	Optimal	2.008	4.651	1.398	0.509
6	FF	8	Non-optimal	2.524	6.039	25.501	75.215
7	Taguchi	2	Non-optimal	3.368	7.436	21.954	76.186
8	FF	8	None	2.524	6.039		
9	FF	2	Non-optimal	3.228	6.594	32.775	111.030
10	FF	2	Optimal	3.228	6.594	0.813	0.370
11	FF	2	None	3.228	6.594		
12	FF	4	Optimal	3.160	6.388	0.819	0.373
13	Taguchi	4	Non-optimal	3.442	7.716	12.295	38.458
14	FF	4	Non-optimal	3.160	6.388	25.570	81.512
15	Taguchi	8	None	2.008	4.651		
16	Taguchi	2	Optimal	3.368	7.436	0.758	0.368
17	FF	8	Optimal	2.524	6.039	1.668	0.749
18	Taguchi	8	Non-optimal	2.008	4.651	14.699	46.375

Table 6.16 Milling case study (1st block) evaluation data set (second phase).

Run	Method	Repetitions	Transformations	Raw data Location	Raw data Dispersion	Transformed data Location	Transformed data Dispersion
1	Taguchi	2	None	20.558	11.589		
2	Taguchi	4	None	20.373	11.214		
3	Taguchi	4	Optimal	20.373	11.214	1.228	0.037
4	FF	4	None	19.77	9.974		
5	Taguchi	8	Optimal	20.47697	11.00205	0.030699	0.011741
6	FF	8	Non-optimal	19.91433	9.949667	502.3252	608.5345
7	Taguchi	2	Non-optimal	20.558	11.589	568.8033	762.8855
8	FF	8	None	19.91433	9.949667		
9	FF	2	Non-optimal	19.803	10.121	500.6979	628.9647
10	FF	2	Optimal	19.803	10.121	1.227	0.038
11	FF	2	None	19.803	10.121		
12	FF	4	Optimal	19.77	9.974	1.227	0.036
13	Taguchi	4	Non-optimal	20.373	11.214	553.9898	737.6987
14	FF	4	Non-optimal	19.77	9.974	498.1795	619.4581
15	Taguchi	8	None	20.47697	11.00205		
16	Taguchi	2	Optimal	20.558	11.589	1.229	0.038
17	FF	8	Optimal	19.91433	9.949667	1.223589	0.034693
18	Taguchi	8	Non-optimal	20.47697	11.00205	548.6083	687.9737

Table 6.17 Traffic flow case study evaluation data set (second phase).

				Raw data		Transformed data	
Run	**Method**	**Repetitions**	**Transformations**	**Location**	**Dispersion**	**Location**	**Dispersion**
1	Taguchi	2	None	23396.579	16940.979		
2	Taguchi	4	None	21016.954	14032.059		
3	Taguchi	4	Optimal	21016.954	14032.059	0.189	0.109
4	FF	4	None	17980.515	13424.242		
5	Taguchi	8	Optimal	13188.03	9097.833	0.022593	0.00577
6	FF	8	Non-optimal	12691.08	8738.039	4.02E+08	4.81E+08
7	Taguchi	2	Non-optimal	23396.579	16940.979	8.19E+08	1.12E+09
8	FF	8	None	12691.08	8738.039		
9	FF	2	Non-optimal	20090.498	16173.523	6.85E+08	9.66E+08
10	FF	2	Optimal	20090.498	16173.523	0.35	0.034
11	FF	2	None	20090.498	16173.523		
12	FF	4	Optimal	17980.515	13424.242	0.354	0.031
13	Taguchi	4	Non-optimal	21016.954	14032.059	7.54E+08	8.69E+08
14	FF	4	Non-optimal	17980.515	13424.242	6.32E+08	7.89E+08
15	Taguchi	8	None	13188.03	9097.833		
16	Taguchi	2	Optimal	23396.579	16940.979	0.186	0.108
17	FF	8	Optimal	12691.08	8738.039	0.14407	0.019178
18	Taguchi	8	Non-optimal	13188.03	9097.833	4.45E+08	5.05E+08

Table 6.18 GA optimisation case study evaluation data set (second phase).

		DF	Seq SS	Adj SS	Adj MS	F Value	P>F
Location	**Method**	1	69.38	69.38	69.38	155.88	0
	Repetitions	2	28.53	28.53	14.27	32.05	0.003
	Transformations	2	1632.45	1632.45	816.22	1833.82	0
	Method*Repetitions	2	0.44	0.44	0.22	0.5	0.642
	Method*Transf.	2	133.62	133.62	66.81	150.1	0
	Repetiti*Transf.	4	57.11	57.11	14.28	32.07	0.003
	Error	4	1.78	1.78	0.45		
	Total	17	1923.31				
Dispersion	**Method**	1	626.4	626.4	626.4	59.64	0.002
	Repetitions	2	510.9	510.9	255.4	24.32	0.006
	Transformations	2	18603.1	18603.1	9301.6	885.57	0
	Method*Repetitions	2	11	11	5.5	0.52	0.628
	Method*Transf.	2	1272.6	1272.6	636.3	60.58	0.001
	Repetiti*Transf.	4	964.9	964.9	241.2	22.97	0.005
	Error	4	42	42	10.5		
	Total	17	22030.9				

Table 6.19 ANOVA test for location and dispersion (on Table 6.16) study for significance of statistical tools – second phase (1^{st} block Milling case study).

		DF	Seq SS	Adj SS	Adj MS	F Value	P>F
Location	Method	1	1623	1623	1623	86.33	0.001
	Repetitions	2	39	39	20	1.04	0.433
	Transformations	2	1075135	1075135	537567	2.90E+04	0
	Method*Repetitions	2	45	45	22	1.2	0.392
	Method*Transf.	2	3206	3206	1603	85.25	0.001
	Repetiti*Transf.	4	69	69	17	0.92	0.531
	Error	4	75	75	19		
	Total	17	1080192				
Dispersion	Method	1	6247	6247	6247	48.01	0.002
	Repetitions	2	788	788	394	3.03	0.158
	Transformations	2	1790129	1790129	895065	6878.87	0
	Method*Repetitions	2	266	266	133	1.02	0.438
	Method*Transf.	2	12082	12082	6041	46.43	0.002
	Repetiti*Transf.	4	1540	1540	385	2.96	0.159
	Error	4	520	520	130		
	Total	17	1811573				

Table 6.20 ANOVA test for location and dispersion (on Table 6.17) study for significance of statistical tools – second phase (Traffic flow case study).

		DF	Seq SS	Adj SS	Adj MS	F Value	P>F
Location	Method	1	4.97E+15	4.97E+15	4.97E+15	12.19	0.025
	Repetitions	2	4.09E+16	4.09E+16	2.04E+16	50.19	0.001
	Transformations	2	1.55E+18	1.55E+18	7.76E+17	1904.43	0
	Method*Repetitions	2	8.15E+14	8.15E+14	4.07E+14	1	0.444
	Method*Transf.	2	9.93E+15	9.93E+15	4.97E+15	12.19	0.02
	Repetiti*Transf.	4	8.18E+16	8.18E+16	2.04E+16	50.19	0.001
	Error	4	1.63E+15	1.63E+15	4.07E+14		
	Total	17	1.69E+18				
Dispersion	Method	1	3.70E+15	3.70E+15	3.70E+15	5.22	0.084
	Repetitions	2	1.02E+17	1.02E+17	5.12E+16	72.31	0.001
	Transformations	2	2.49E+18	2.49E+18	1.24E+18	1753.89	0
	Method*Repetitions	2	1.42E+15	1.42E+15	7.09E+14	1	0.444
	Method*Transf.	2	7.40E+15	7.40E+15	3.70E+15	5.22	0.077
	Repetiti*Transf.	4	2.05E+17	2.05E+17	5.12E+16	72.31	0.001
	Error	4	2.83E+15	2.83E+15	7.09E+14		
	Total	17	2.81E+18				

Table 6.21 ANOVA test for location and dispersion (on Table 6.18) study for significance of statistical tools – second phase (GA optimisation case study).

	Factor	Levels	Mean	Std. Dev.
Location	Method	FF	10.6731	0.2224
		Taguchi	6.7466	
	Repetitions	2	10.4827	0.2724
		4	7.6805	
		8	7.9663	
	Transformations	None	2.955	0.2724
		Non-optimal	22.1323	
		Optimal	1.0422	
Dispersion	Method	FF	32.03	1.0803
		Taguchi	20.2318	
	Repetitions	2	33.664	1.3231
		4	22.4723	
		8	22.2563	
	Transformations	None	6.4707	1.3231
		Non-optimal	71.4627	
		Optimal	0.4593	

Table 6.22 Least Squares Means for Location and Dispersion (on Table 6.16) study for significance of statistical tools – second phase (1^{st} block of milling case study).

	Factor	Levels	Mean	Std. Dev.
Location	Method	FF	173.819	1.445
		Taguchi	192.811	
	Repetitions	2	185.386	1.77
		4	182.461	
		8	182.097	
	Transformations	None	20.149	1.77
		Non-optimal	528.767	
		Optimal	1.028	
Dispersion	Method	FF	209.679	3.802
		Taguchi	246.939	
	Repetitions	2	235.606	4.657
		4	229.736	
		8	219.584	
	Transformations	None	10.642	4.657
		Non-optimal	674.253	
		Optimal	0.033	

Table 6.23 Least Squares Means for Location and Dispersion (on Table 6.17) study for significance of statistical tools (Traffic flow case study) – second phase.

	Factor	Levels	Mean	Std. Dev.
Location	Method	FF	1.91E+08	6727854
		Taguchi	2.24E+08	
	Repetitions	2	2.51E+08	8239904
		4	2.31E+08	
		8	1.41E+08	
	Transformations	None	18061	8239904
		Non-optimal	6.23E+08	
		Optimal	0	
Dispersion	Method	FF	2.48E+08	8873584
		Taguchi	2.77E+08	
	Repetitions	2	3.48E+08	10867877
		4	2.76E+08	
		8	1.64E+08	
	Transformations	None	13068	10867877
		Non-optimal	7.88E+08	
		Optimal	0	

Table 6.24 Least Squares Means for Location and Dispersion (on Table 6.18) study for significance of statistical tools – second phase (GA Optimisation case study).

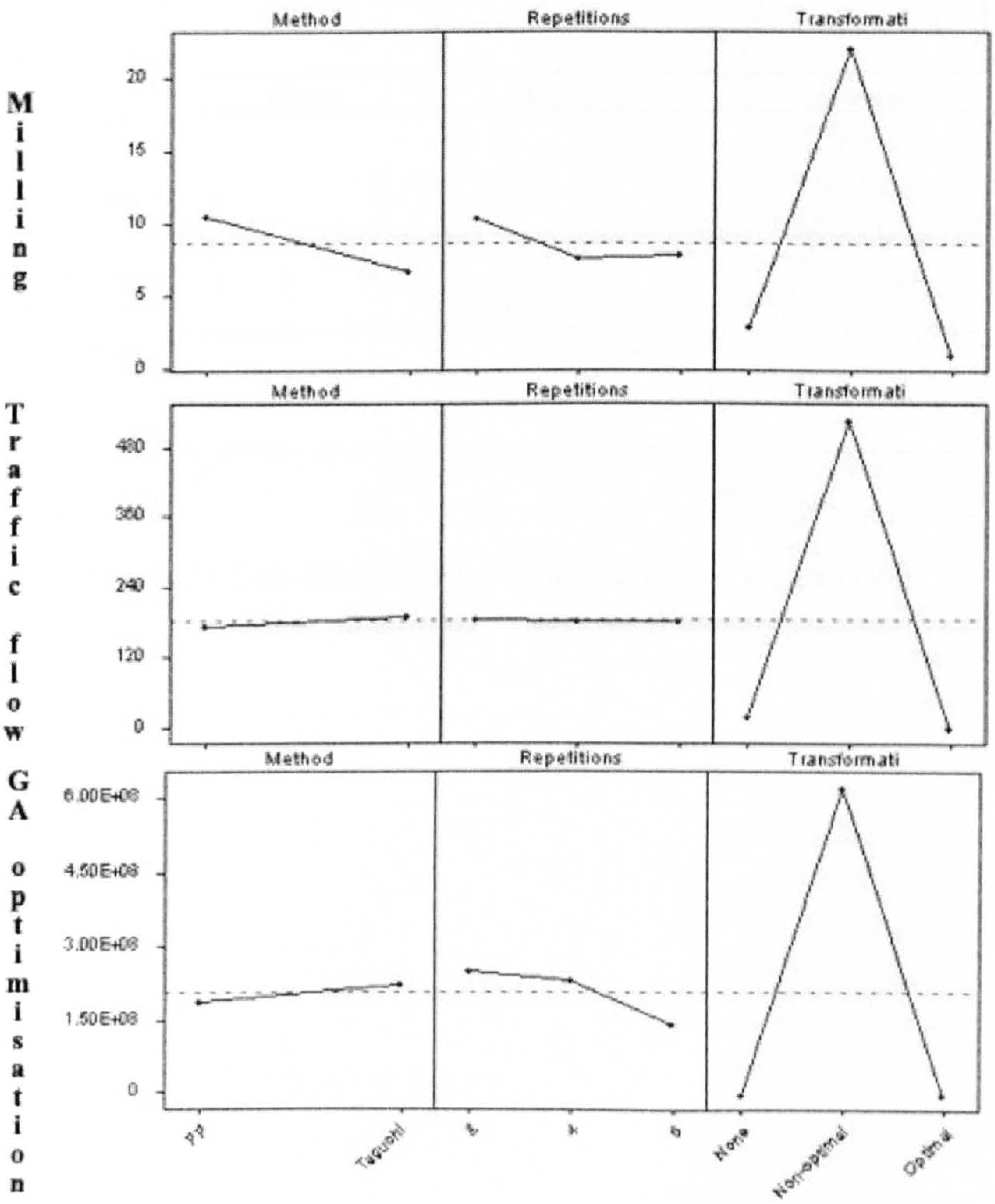


Fig. 6.13 Dot-line plots for main factors – Location (all case studies in second phase).

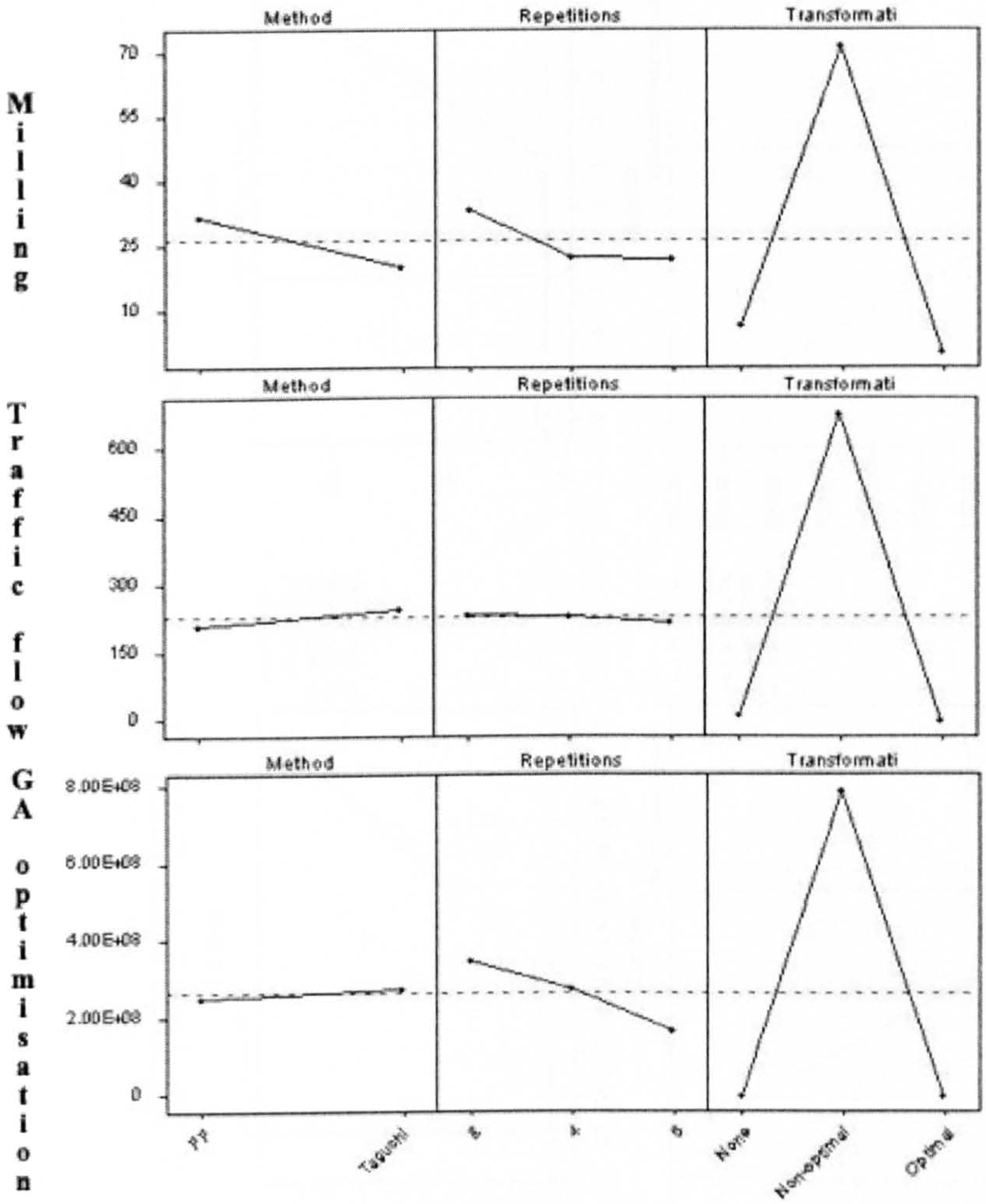


Fig. 6.14 Dot-line plots for main factors – Dispersion (all case studies in second phase).

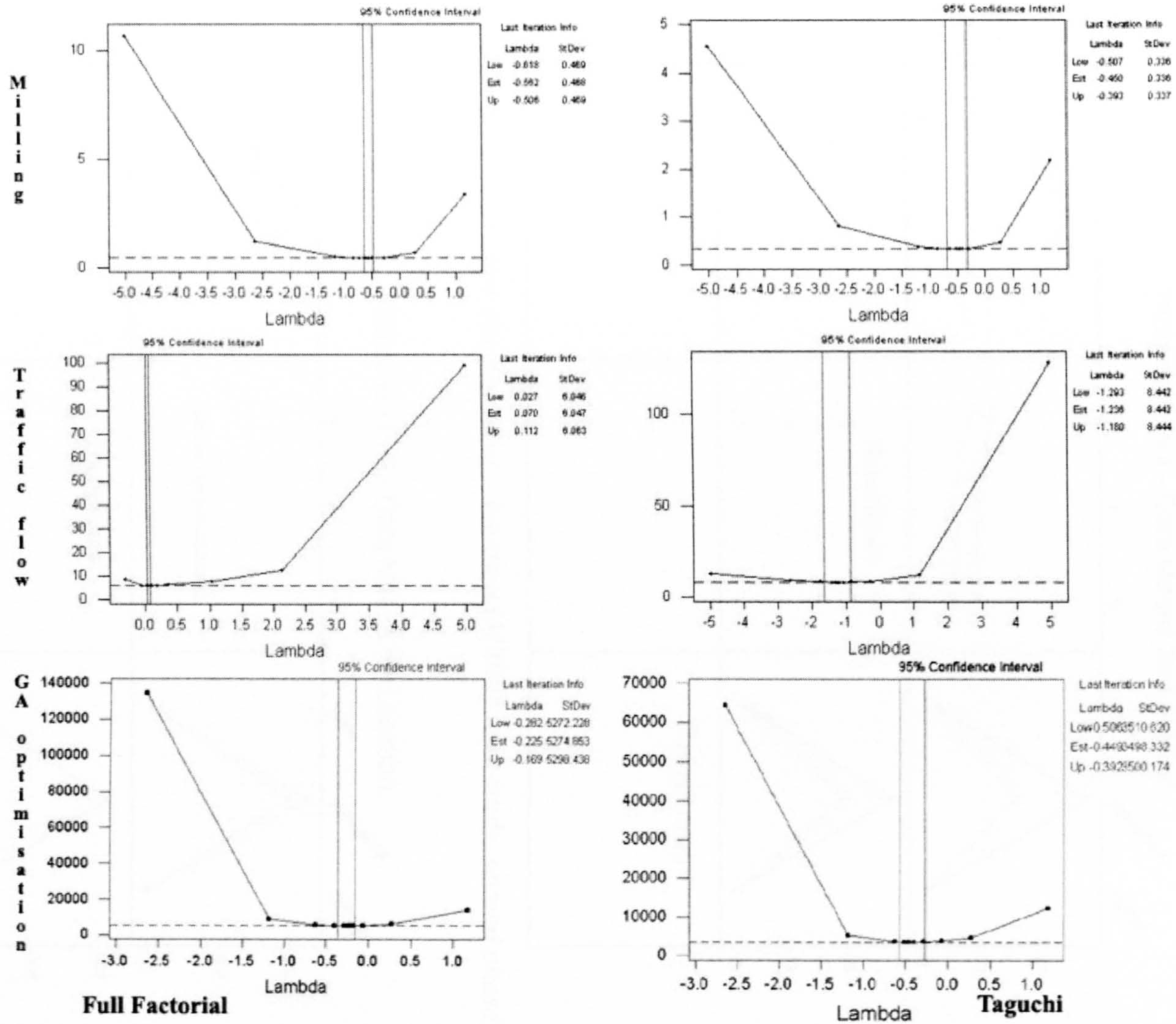


Fig. 6.15 Plots for determining the optimal transformation with the Box-Cox method – all cases, second phase.

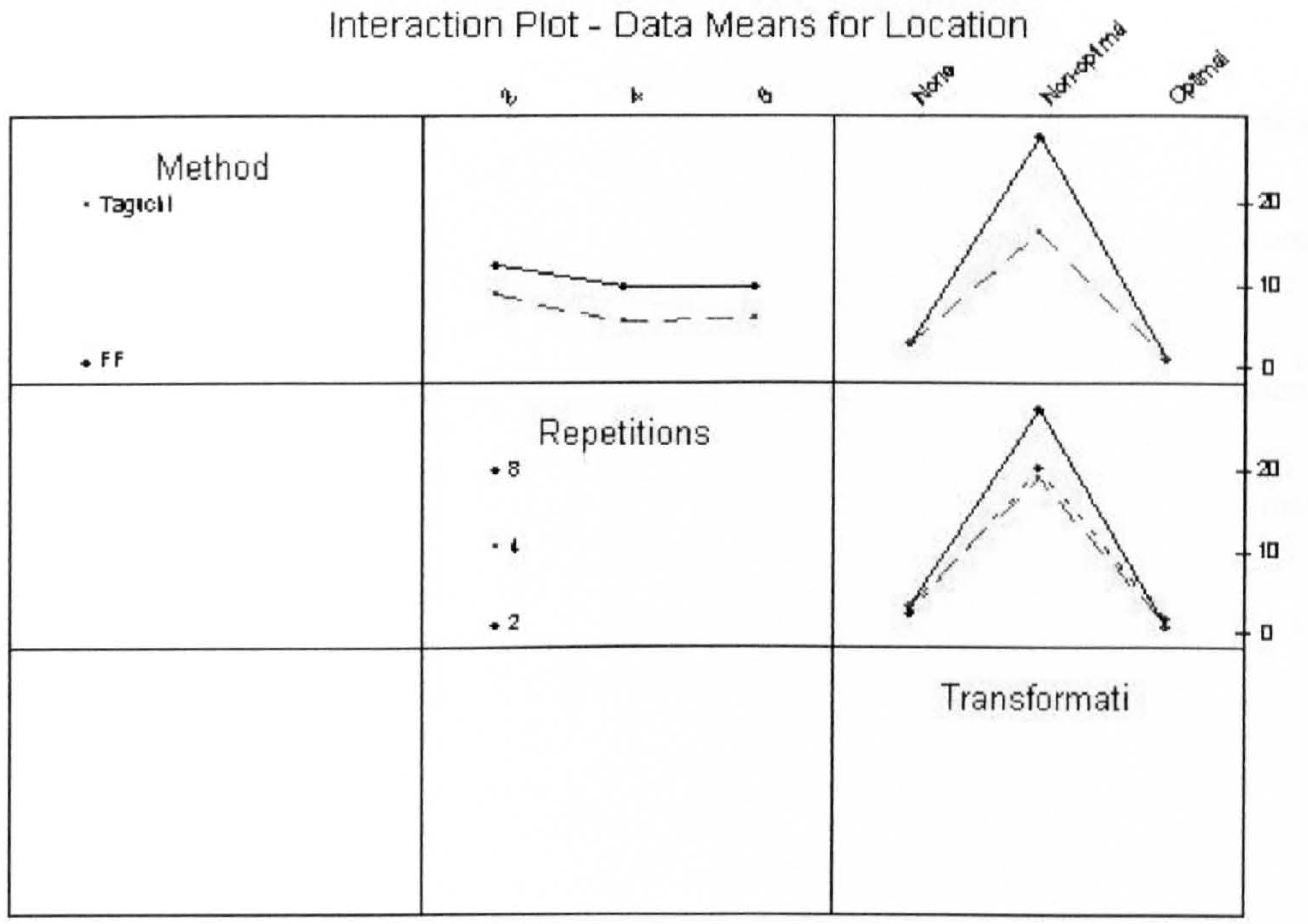


Fig. 6.16 Interaction dot-line plots – location (Milling case study, second phase).

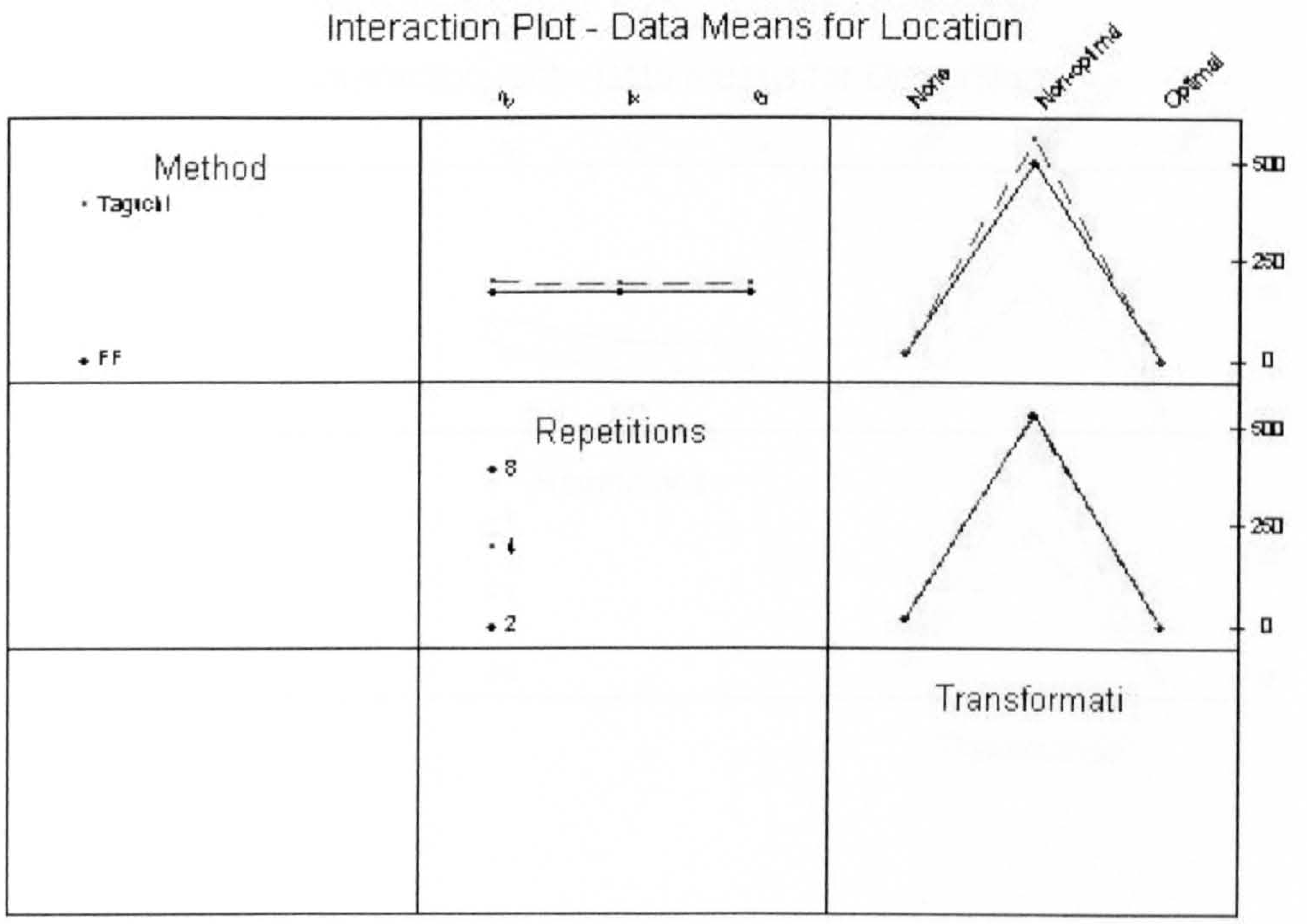


Fig. 6.17 Interaction dot-line plots – location
(Traffic flow case study, second phase).

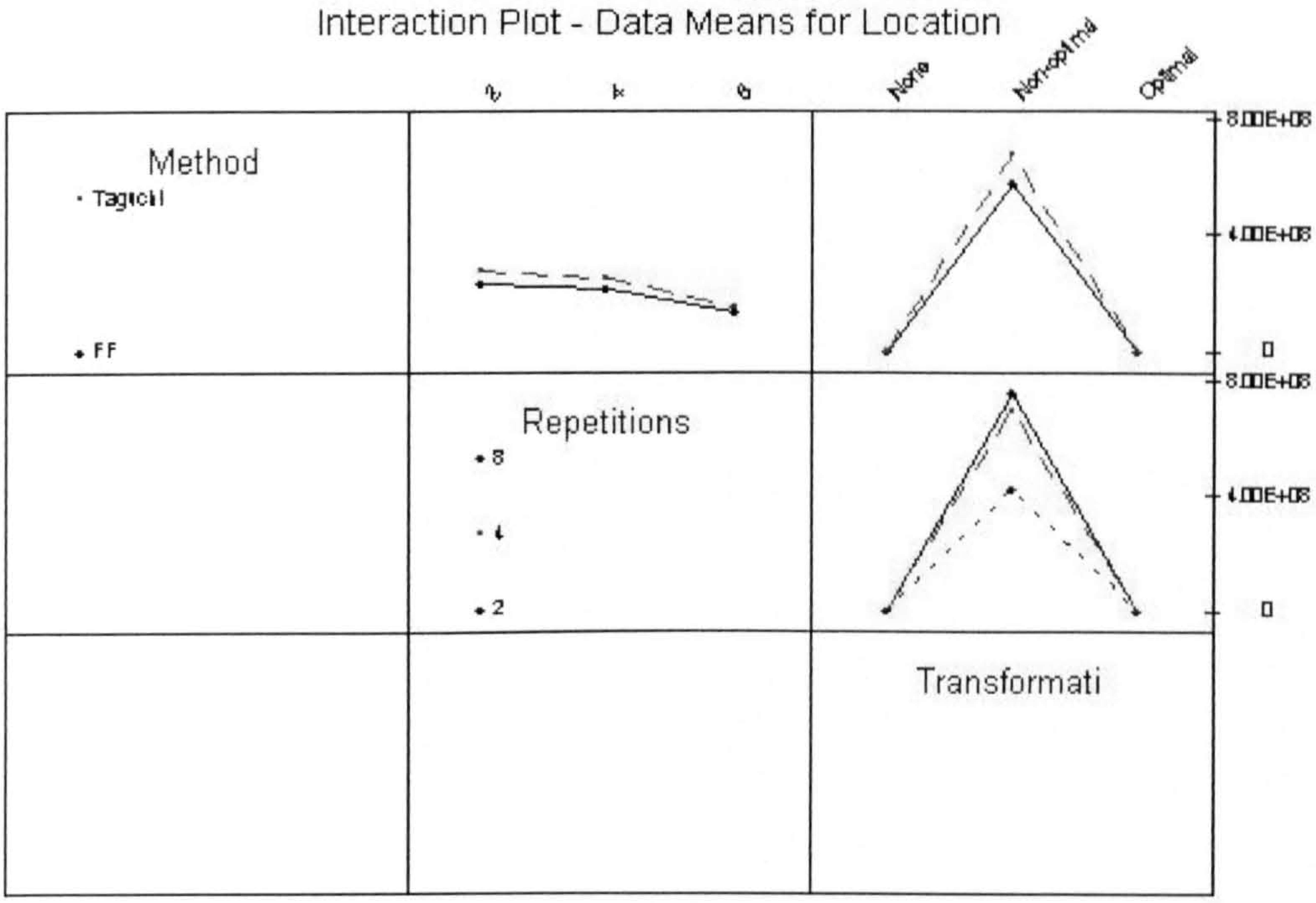


Fig. 6.18 Interaction dot-line plots – location (GA optimisation case study, second phase).

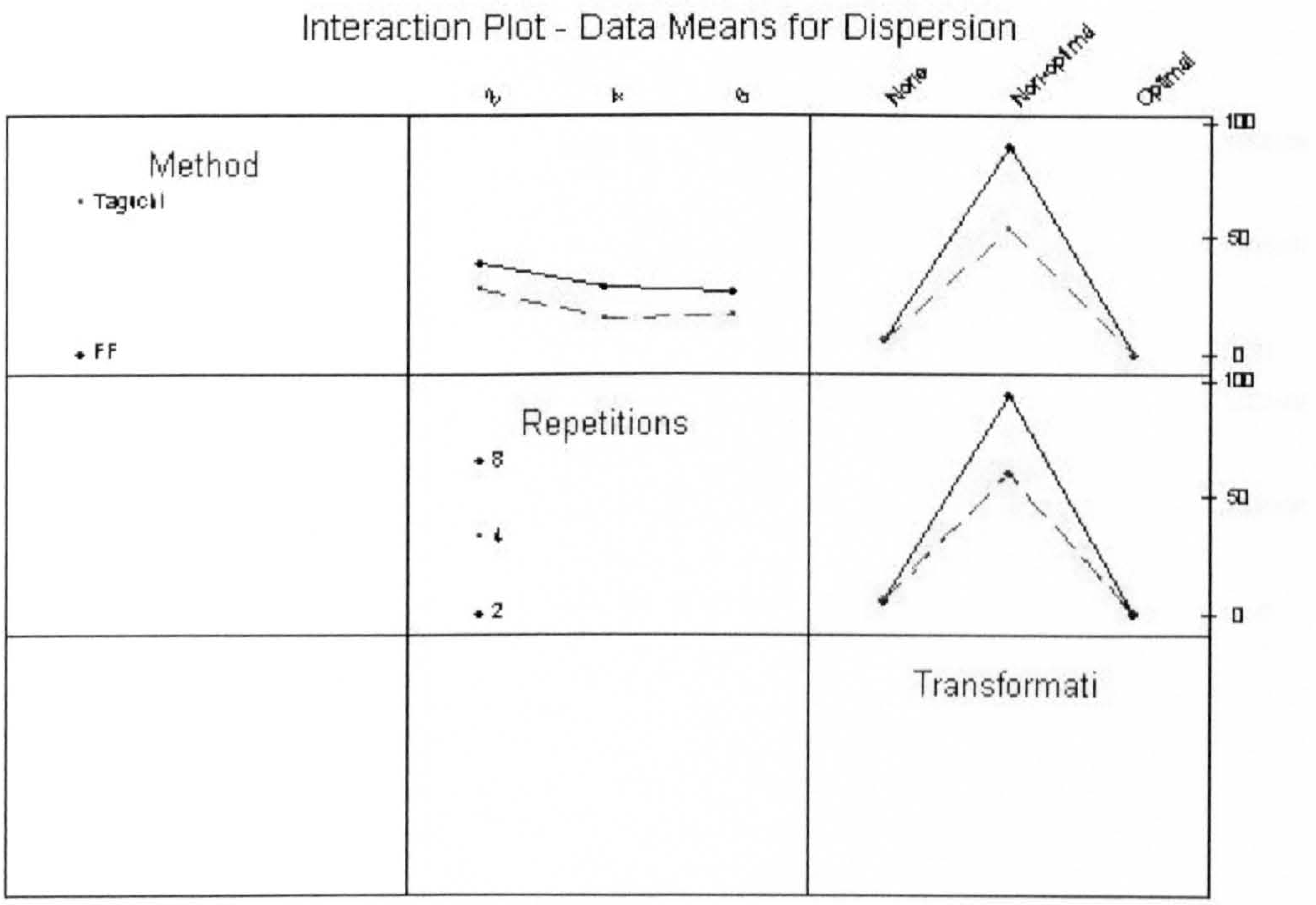


Fig. 6.19 Interaction dot-line plots – dispersion (milling case study, second phase).

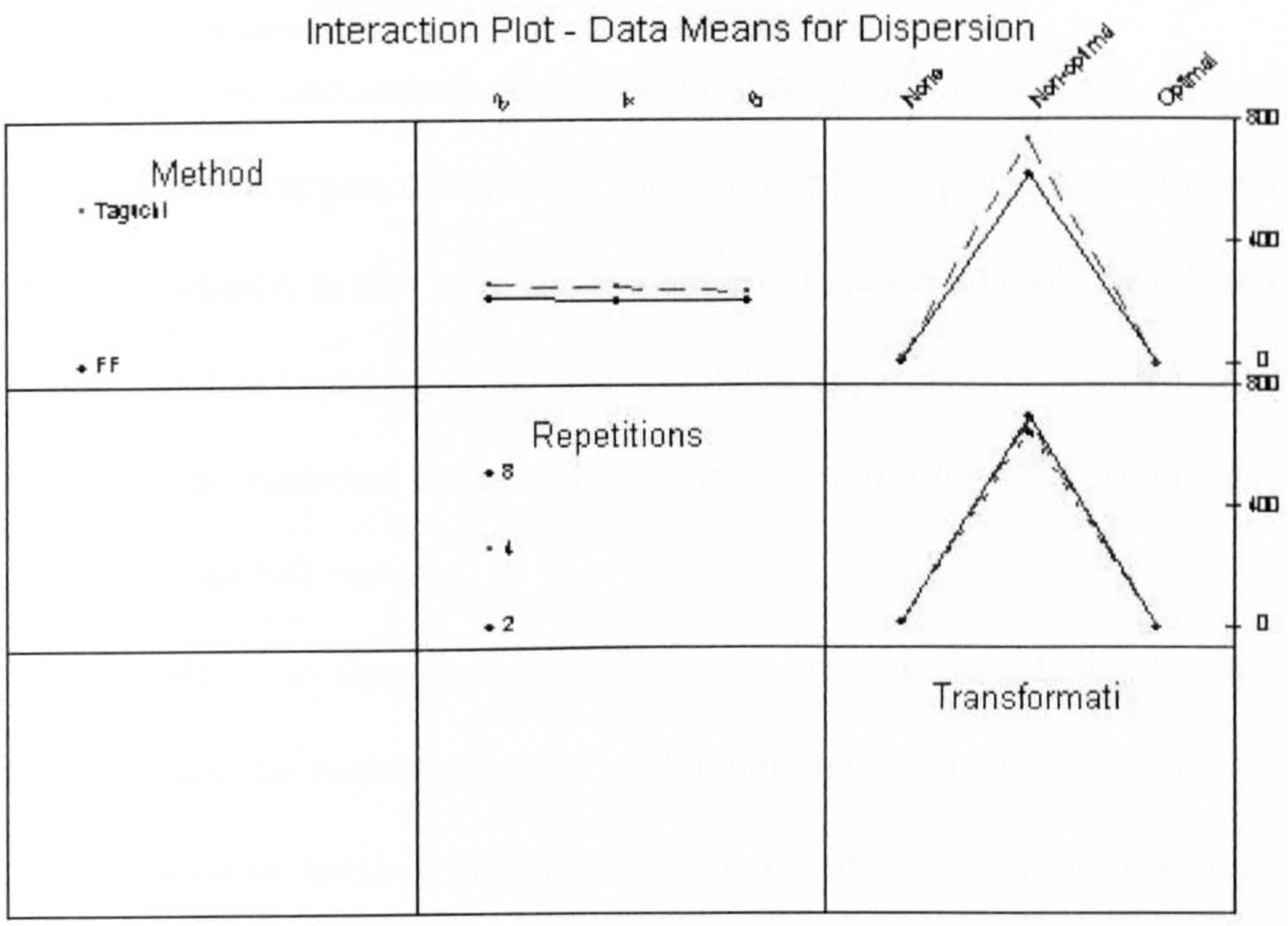


Fig. 6.20 Interaction dot-line plots – dispersion (Traffic flow case study, second phase).

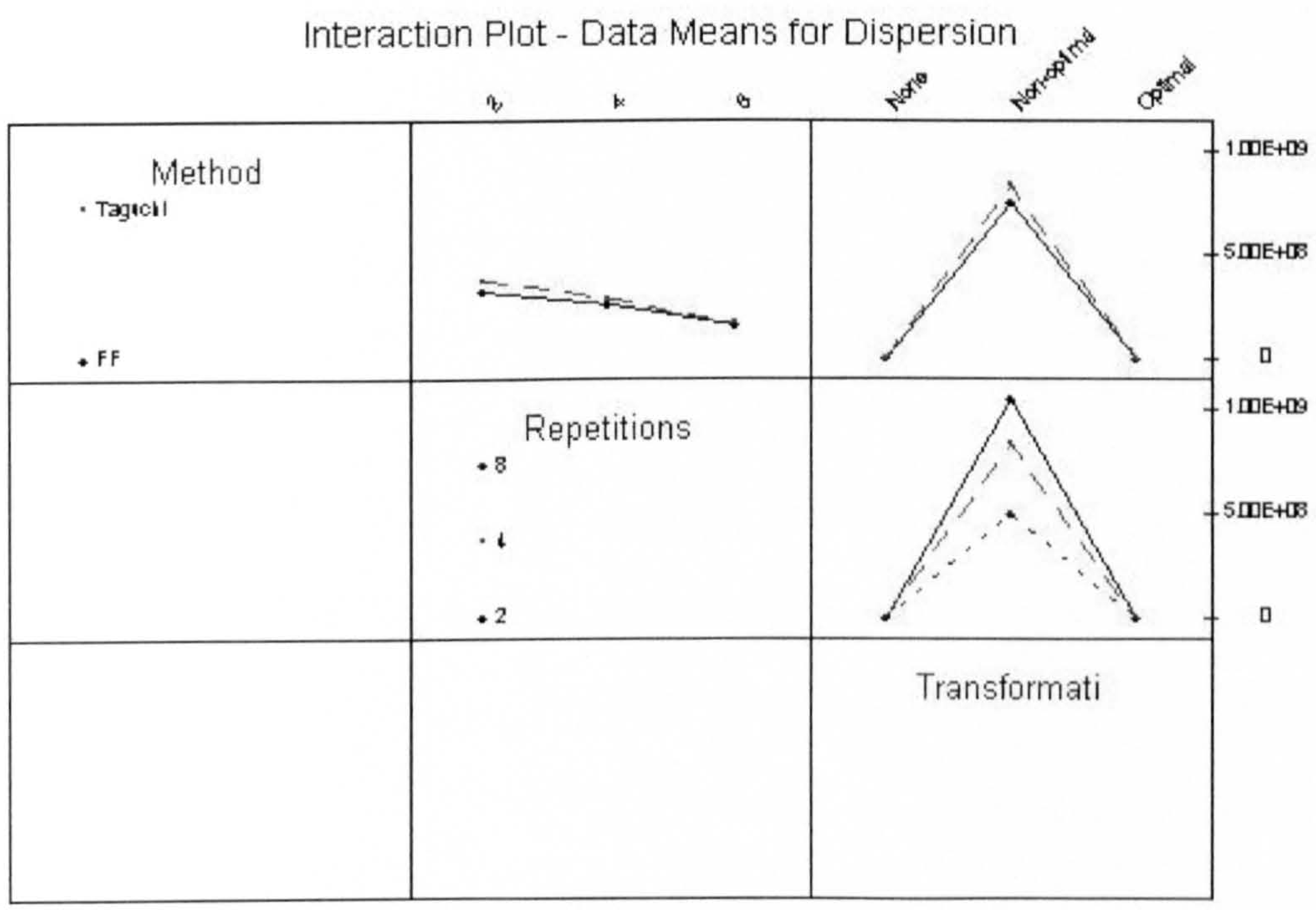


Fig. 6.21 Interaction dot-line plots – dispersion (GA optimisation case study, second phase).

6.5 Recommendations for further study

Since tool interactions were found throughout this study, it would be interesting to investigate the incorporation of problem types as factors into a wider array. For instance, in this case, the evaluation of statistical tools was done on two different problem types (physical and simulated experiments), which may well be included as an additional factor to test their compatibility with certain array types (eg Taguchi and full factorial).

In addition to this, further testing may be done in relation to the use of repetitions and the incorporation of additional statistical tools, ie randomisation. This may involve seeking an alternative to estimate a way of determining the adequate number of repetitions for a specific problem simpler than the usual complex statistical formulas for determining sample size.

Chapter 7

Conclusions

This investigation has shown that product and process optimisation approaches based on Taguchi methodologies (and, in the future, Genetic Algorithms) offer benefits within the industrial and engineering environments. These benefits come from the individual advantages of each, eg economic experimentation and powerful search mechanisms, and with the potential for integration of both providing users with competitive tools. However, this study has also shown that users should always be aware of the mishaps and potential issues associated with the use of both technologies identified during this investigation.

7.1 Taguchi

The issues associated with the implementation of Taguchi tools have been openly discussed in the literature. The findings in this investigation agree in some ways but not entirely with what has been pointed out there. These findings provide answers to the specific objectives (1)-(4) proposed in the Introduction (Chapter 1) and address some of the major issues related to Taguchi tools. Evidence from these case studies reinforces and extends the conclusions previously arrived at by Taher (1995).

7.1.1 Control parameters to reduce dispersion

For the three cases studied here, factors may often show linked behaviour between mean and variation (Tables 3.5, 3.13, 4.5 and 5.7) with the factors influencing dispersion most also strongly influencing location. A similar conclusion can be drawn from a review of the previous three cases studied by Taher (1995) (Table 7.1).

This evidence must question Taguchi's belief in the possibility of finding controllable parameters within the experiment which reduce dispersion without affecting location as much. While this does not diminish the importance of controlling the effects of variation, it does suggest that in many cases the quality strategy must involve optimising location in the first instance. Taguchi's SNR metric is based to some extent on his concept of controlling dispersion without affecting location and therefore this conclusion must cast some philosophical doubt on the SNR concept. However, it must be acknowledged that the case studies in this work and in Taher (1995) included only LTB and STB and not Nominal-the-Better (target) objectives.

Factors	**Turning**		**Dental Plaster**		**High Alumina Cement**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
A	**1**	**2**	**1**	**1**	**1**	4
B	**2**	**1**	**2**	5	**2**	1
C	**3**	4	3	7	**3**	**2**
D	4	5	4	3	**4**	5e
E	5	**3**	5	4	**5**	7
F			6	**2**	6	**3**
G					7	5e

Table 7.1 A review of factor ranking for effects on location and dispersion for the three case studies in Taher (1995) (N.B. bold numbers denote significance)

7.1.2 Signal-to-Noise Ratio

The use of SNR has been confirmed as inappropriate for all cases throughout this work and Taher's (1995). SNR direct correlation to mean and weak correlation to STD in most cases (Table 6.2) makes it very unlikely for users to achieve variation reduction using this combined metric estimator. In the case where it was not strongly correlated with the mean (Chapter 5) it was not found to identify the factors which control dispersion. Coupled with the above conclusions on controlling the effects of variation, this indicates that it will generally be necessary to model the effects of location and dispersion separately in a multi-objective optimisation. Again, though, it must be acknowledged that the case studies so far have only included LTB and STB SNR.

Apart from the evaluation of Taguchi tools, Taher's (1995) suggested approach for combining Taguchi and non-Taguchi tools has brought positive results in this investigation. Using the power of optimal data transformations and factor/level analysis techniques, the performance of Taguchi arrays can be enhanced up to matching levels of performance (for location and dispersion effects) of conventional designs (ie full factorial) (Section 6.4). This investigation has also shown that in most cases these two tools should be enough and that the use of a higher number of repetitions would not bring the necessary tradeoffs between cost (implied in a larger sample size) and performance (Section 6.4). However, unlike differing choices for linear graphs, the choice of transformation is not robust, and a non-optimal transformation may give worse results (Chapter 6). Within the context of these case studies, the use of robust statistics was not shown to give benefits over normal statistics. Only for experiments with outliers expected (eg due to failures) might these be expected to make a useful contribution.

7.1.3 Taguchi arrays

Despite many criticisms from statisticians concerning highly fractionated arrays, in practice these case studies show that the use of Taguchi arrays seems to offer relatively adequate performance compared to conventional designs (full factorial) for identifying important factors (but not necessarily correctly ranked) and the best factor combinations in the cases investigated. However, at the same time Taguchi's dismissive approach to these criticisms may be wrong, as his assumptions about the unimportance of interactions are shown to be erroneous and writing off interactions may not pay off on some occasions.

Though Taguchi arrays did not completely match the power of full factorial designs, Taguchi array performance was nearly as strong as full factorial designs in determining the main factor effects, though not always correctly ranked, but it is usually not possible to detect whether the Taguchi model and these effects are significant. Taguchi arrays may also identify best factor-level combinations similar or close to those predicted by full factorial experiments, though these may be more reliable for location than for dispersion. However, the best combinations are often not from those combinations included in the Taguchi arrays so factor-level analysis is essential.

Taguchi arrays may therefore be adopted as screening arrays in a sequential experiment strategy, as suggested previously by Taher (1995). For example, the traffic flow experiment (Chapter 4) served as a "test bed" for the implementation of DoE through Taguchi tools into large sized computer experiments. The results suggested that determination of significant effects/factors through this approach has paid off since it helped to identify theoretically important factors, such as speed distribution, surprisingly found here unimportant, as well as those significant ones (vehicle mix and some profiles) at a level that may be interesting to test the following step of a sequential approach (eg RSM).

However, this conclusion is despite the evidence from all case studies of the significance that interaction effects have on products. For instance, in some cases (milling – Chapter 3), interactions may account for over half of the effects and significant third-order interactions have been found. In at least one of the case studies (GA parameter optimisation- Chapter 5), significant interactions have been found involving non-significant main factors. Situations like these may be problematic within the industrial context as investing resources on minimising the effect of non-significant main factors (involved in significant interactions), as Taguchi suggests, may be a resource waste and therefore non-viable. This may be a tough and (sometimes) risky decision to take for experimenters and it is also difficult to provide a solution for this dilemma as it arises on a case-by-case basis.

7.1.4 Other Taguchi tools

Results obtained suggested that the application of linear graphs was not as significant as expected. Taguchi tools for compensating for the reduced degrees of freedom with his arrays, ie the application of linear graphs for interaction and aliasing structures handling, are not the reason why his arrays seem to perform well. Though their investigation was not as extensive as with the other tools, linear graphs did not seem to make much difference whether they were used or not (Chapter 3). This may be seen as positive (the similar results may suggest robustness in the array designs) or negative (application of the tool has little influence on the results) for Taguchi at the same time. All the case studies showed significant interactions with often considerable influence, but even where there is a substantial existing literature on factor effects (eg milling, GAs or the three cases in Taher (1995)), this rarely discusses interaction effects, so the practicality of these tools must be questionable.

Despite (or because of) the extent of material generated in this investigation (in order to provide a range of applications) there was not enough time to research many interesting aspects of Taguchi methods, Elements such as Inner-Outer arrays and linear graphs or different resolution Taguchi arrays (eg L_8 compared with L_{16} or L_{32} fractions), which had little or no coverage in this work, remain as likely candidates for an extension of this work in relation to Taguchi implementations.

With Taguchi tools obtaining such mixed positive and negative results, the experience collected in this study may be enough to suggest that experimenters do not follow Taguchi suggestions blindly but stop, think and analyse their products and processes (there is no replacement for experimenters' knowledge of the process). For instance, they should ask themselves: is this happening only for one response? What may happen if I try to add more responses? They may face an extra obstacle here, as Taguchi does not provide a clear methodology for handling multi-response optimisation (Section 2.4) though Taher (1995) has suggested RSM in a sequential experimentation approach following a Taguchi screening array.

7.2 Genetic Algorithms

The other half of this investigation, concerning the implementation of GAs for product and process optimisation, demonstrated that minimising the effort for finding initial nominal parameter settings for complex simulated experiments is viable with the help of DoE techniques. The importance of this lies in the fact that a significant part of the cost in engineering design is the time required to find initial settings, which in this case was finding the initial GA parameters for optimising the GA search power. Only a few GA parameters were chosen for testing this optimisation approach. However, the intention was to provide a methodology which users can adapt to their own problems. Therefore, an implementation considering a greater number of parameters may be perfectly feasible if the suggested enhancing measures for Taguchi arrays are taken into consideration. The value of this lies in the conclusion from Chapter 5, which contradicts generally held views about simple GAs, that they are not necessarily robust to their parameter settings or choice of initial populations (ie setting seeds), at least not for this particular combinatorial problem.

One of the most important outcomes related to the GA parameters under study was the lack of significance of a well-known parameter such as crossover probability. In fact, other less publicised operators, such as the rate size/winners of tournament selection, were found to have greater impact on finding the optimal solution (or near optimal) than crossover probability itself. This may be an artefact of the combinatorial problem selected for illustration (OOBF). As this contains relatively little information on the structure of the solution, it may be that crossover does not work in the same way for this type of problem as it does in others. Further investigation with a wider range of problem types (as done for Taguchi) is recommended.

Also, the GA parameter optimisation methodology investigated still has plenty of applications and parameters that can be compared and evaluated. Most advanced operators that were left aside after the brainstorming stage (Chapter 5) may make an interesting pool of candidates to get started with. In addition, performance enhancing techniques (like hashing tables (Section 5.5)) may become very promising alternatives, if performance (eg convergence rate) is an additional focus of optimisation. DoE represents an alternative to evolutionary optimisation of GA parameters which focuses attention on the actual contributions of the parameters and their interactions. At the same time this optimisation mechanism may be extended to other random search techniques (eg Simulated Annealing and Tabu Search).

GA may address multiobjective optimisation problems using, eg, the desirability index approach adopted by Taher (1995) for use with RSM. Taking advantage of the multiobjective optimisation capabilities of GAs, it would be interesting to investigate an approach where the focus is to assess the product and process improvements through cost. Within this context, a framework where sequential experimentation is combined with GAs, as reviewed here, to evaluate different cost/implementation scenarios may also be worth investigating.

Recommendations for further study

Apart from those recommendations already made after the evaluation of each case study, the following global suggestions may also be of some interest:

- Despite of the extent of material generated in this investigation there was not enough time to research most interesting "nodes" of this work. Elements such as Inner-Outer arrays and linear graphs, which had none or little coverage in this work, remain as very likely candidates for an extension of this work in relation to Taguchi methods implementation.

- Taking advantage of the multiobjective optimisation capabilities of GAs it would be interesting to investigate an approach where the focus is to assess the product and process improvements through cost. Cost based approaches may have an appealing. Within this context, a framework where sequential experimentation is combined with GAs, as reviewed here, to evaluate different cost/implementation scenarios may also be worth investigating.

- The GA parameter optimisation methodology investigated still has plenty of applications and parameters that can be compared and evaluated. Most advanced operators that were left aside after the brainstorming stage (Chapter 5) may make an interesting pool of candidates to get started with. In addition to it, performance enhancing techniques (like hashing tables (Section 5.5)) may become very promising alternatives, if preformance is the additional focus of optimisation, thanks to their journaling capabilities which can be also optimised. At the same time this optimisation mechanism may be extensive to other random search techniques (eg Tabu Search).

- The DoE approach applied in this work for evaluating those Taguchi and non-Taguchi tools can be used for evaluating other important quality (or quality-related) methodologies. This may befit the assessment of significant philosophies (ie Six Sigma, Kaizen and Kanban) or alternatively some of their key elements/tools.

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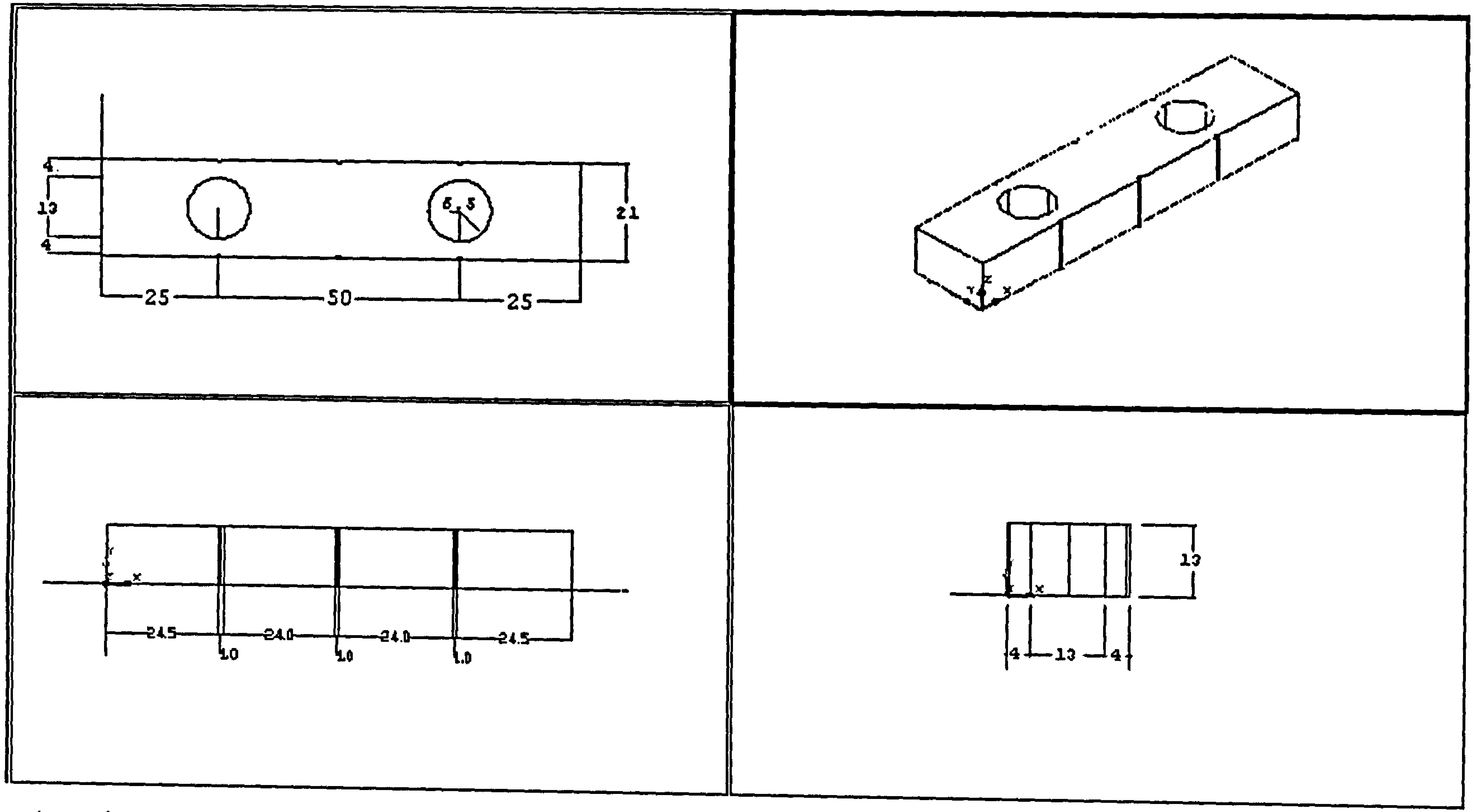
APPENDIX A1
WORKPIECE DESIGN SPECIFICATIONS



Appendix A2 Workpiece design specifications (Viewpoints starting top-left clockwise: plane XY, Isometric, plane XZ and plane YZ).

APPENDIX A2
CNC MACHINE INSTRUCTION SET

The following instruction set is specific to the Cincinnati Milacron Arrow CNC machine model 750 (Cincinnati Milacron, 1994).

```
(CONVENTIONAL MILLING WITH ONE CUT)
(                                          )
(ALUMINUM SPECIMEN FOR SURFACE FINISH ASSESMENT)
G0 G90 G57 G71 G40
T12 M6 (20 DIA STANDARD LENGTH (4-FLUTE))
G43 Z100 H12
F203 S2700 M3
' SIDE 2 - CONV - NO COOLANT
X-35 Y-21.7
Z15
G1 Z0
X0
G4 X1
X25
G4 X1
X50
G4 X1
X80
' SIDE 1
X100F3000
Y21.7
X80
X50F203
G4X1
X25
G4 X1
X0
G4 X1
X-30
G0 Z100
Y200
M30
```

```
(CONVENTIONAL MILLING WITH TWO CUTS)
(                                        )
(ALUMINUM SPECIMEN FOR SURFACE FINISH ASSESMENT)
G0 G90 G57 G71 G40
T12 M6 (20 DIA STANDARD LENGTH (4-FLUTE))
G43 Z100 H12
F203 S2700 M3
' SIDE 2 – CONV – NO COOLANT
X-35 Y-22.2
Z15
G1 Z0
X80
' SIDE 1
X100F3000
Y22.2
X80
X50F203
X-30
' SIDE 2
X-50 F3000
Y-21.7
X-35
X0 F203
G4 X1
X25
G4 X1
X50
G4 X1
X80
' SIDE 1
X100F3000
Y21.7
X80
X50F203
G4 X1
X25
G4 X1
X0
G4 X1
X-30
G0 Z100
Y200
M30
```

```
(CLIMB MILLING WITH ONE CUT)
(                                          )
(ALUMINUM SPECIMEN FOR SURFACE FINISH ASSESMENT)
G0 G90 G57 G71 G40
T12 M6 (20 DIA STANDARD LENGTH (4-FLUTE))
G43 Z100 H12
F330 S2700 M3
' SIDE 1 – CLIMB MILLING – NO COOLANT
X-35 Y21.7
Z15
G1 Z0
X0
G4 X1
X50
G4 X1
X80
' SIDE 2
X100F3000
Y-21.7
X80
X50F330
G4 X1
X25
G4 X1
X0
G4 X1
X-30
G0 Z100
Y200
M30
```

```
(CLIMB MILLING WITH TWO CUTS)
(                                        )
(ALUMINUM SPECIMEN FOR SURFACE FINISH ASSESMENT)
G0 G90 G57 G71 G40
T12 M6 (20 DIA STANDARD LENGTH (4-FLUTE))
G43 Z100 H12
F203 S2700 M3
' SIDE 1 – CLIMB MILLING – COOLANT
X-35 Y22.2
Z15
G1 Z0
X0
X25
X50
X80
' SIDE 2
X100F3000
Y-22.2
X80
X50F203
X25
X0
X-30
X-50 F3000
Y21.7
' SIDE 1 REPEAT
X-35
X0 F203
G4 X1
X25
G4 X1
X50
G4 X1
X80
' SIDE 2 REPEAT
X100F3000
Y-21.7
X80
X50F203
G4 X1
X25
G4 X1
X0
G4 X1
X-30

G0 Z100
Y200
M30
```

APPENDIX B1

FULL FACTORIAL DATA SET FOR PERPENDICULAR MEASUREMENT METHOD FEATURING SURFACE ROUGHNESS RESPONSE

Abbreviations

Run – run number.

Factors:
TS - Tool speed (rev/min).
WS – Workpiece Travelling speed (mm/min).
DC – Depth of cut (mm).
C – Coolant.
DIC – Direction of Cut.
    Climb – Climbing milling
    Conv. – conventional milling.
CL – Number of Cuts.

Repetitions:
R1 – Repetition One.
R2 – Repetition Two.
R3 – Repetition Three.
R4 – Repetition Four.
R5 – Repetition Five.
R6 – Repetition Six.
R7 – Repetition Seven.
R8 – Repetition Eight.

Responses (Stats calculated for each run only):
Mean – Mean.
STD – Standard Deviation.
SNR – Signal-to-Noise Ratio.

Notes:
N.A. – Data Not Available.
In all cases the non-availability of data was due to extreme values (high) of surface roughness, so the tester (Mitutoyo, 1989) was unable to report any measurement. N.A. measures were treated as missing values and therefore ignored for purposes of calculating statistics. This means that metrics (responses) were calculated considering only those repetitions with non-missing values.

Run	TS	WS	DC	C	DIC	CL	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	SNR
1	2700	330	1	off	climb.	1	1.273	1.23	1.263	1.247	1.263	1.25	1.217	1.167	1.239	0.03431	-1.863
2	2700	203	1	off	conv.	1	2.003	2.03	2.49	4.457	3.44	3.007	2.473	4.517	3.052	1.00490	-10.086
3	2700	203	1	on	climb.	2	1.003	0.97	0.973	0.967	0.97	0.923	0.907	0.867	0.948	0.04447	0.460
4	2700	203	0.5	off	climb.	1	1.053	1.03	1.057	1.063	1.03	1.037	1.013	1.05	1.042	0.01692	-0.355
5	2700	330	1	on	conv.	1	0.933	0.907	0.913	0.913	0.88	0.923	0.89	0.897	0.907	0.01741	0.846
6	3200	203	1	off	climb.	2	1.223	1.19	1.18	1.177	1.14	1.173	1.18	1.123	1.173	0.03045	-1.390
7	2700	203	0.5	off	climb.	2	1.073	1.003	1.073	1.087	1.09	1.09	1.073	1.047	1.067	0.02943	-0.566
8	2700	330	0.5	off	climb.	2	1.203	1.118	1.19	1.257	1.173	1.123	1.12	1.14	1.166	0.04960	-1.337
9	2700	203	1	on	conv.	2	0.99	0.947	0.967	0.98	0.967	0.953	0.947	1.017	0.971	0.02410	0.253
10	3200	330	1	on	conv.	2	0.947	0.923	0.967	0.887	0.87	0.907	0.93	0.897	0.916	0.03209	0.757
11	2700	203	0.5	on	conv.	2	0.957	0.913	0.897	0.93	0.897	0.887	0.903	0.92	0.913	0.02256	0.788
12	2700	203	0.5	on	conv.	1	0.907	0.907	0.883	0.823	0.837	0.873	0.89	0.867	0.873	0.03055	1.171
13	2700	330	0.5	on	conv.	2	0.93	0.93	0.97	0.94	0.98	0.967	1.013	0.923	0.957	0.03125	0.381
14	2700	203	0.5	off	conv.	1	1.207	1.547	1.41	2.013	1.49	2.15	1.367	1.637	1.603	0.32385	-4.249
15	3200	203	1	on	climb.	2	1.023	1.03	1.03	1.13	0.973	1	1.013	0.997	1.025	0.04680	-0.218
16	3200	203	0.5	on	conv.	2	0.78	0.78	0.863	0.897	0.823	0.763	0.83	0.807	0.818	0.04546	1.735
17	2700	203	1	off	climb.	1	1.037	0.963	1.003	0.99	0.93	0.973	1.013	0.94	0.981	0.03664	0.160
18	3200	203	0.5	off	conv.	1	1.47	1.407	1.33	1.147	2.69	2.363	2.323	2.147	1.86	0.58373	-5.748
19	2700	330	0.5	on	climb.	2	1.29	1.22	1.27	1.157	1.28	1.223	1.17	1.207	1.227	0.04963	-1.784
20	3200	203	0.5	on	climb.	1	1.113	1.063	0.973	0.983	1.057	0.987	0.973	0.963	1.014	0.05568	-0.132
21	3200	203	1	off	climb.	1	1.08	1.063	0.907	0.93	1.017	1.02	0.947	0.94	0.988	0.06532	0.088
22	2700	330	1	on	conv.	2	0.907	0.893	0.84	0.97	0.863	0.823	0.823	0.85	0.871	0.05022	1.186

Appendix B1. Full factorial data set for perpendicular measurement method.....continued

Run	TS	WS	DC	C	DIC	CL	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	SNR
23	2700	203	0.5	on	climb.	1	1.063	0.99	0.973	0.94	1.09	0.957	0.94	0.917	0.984	0.06179	0.127
24	2700	330	0.5	off	conv.	2	4	6.7	8	2.7	8.2	4	8.2	4.2	5.75	2.26148	-15.745
25	2700	203	1	on	climb.	1	0.953	0.957	1.03	1.02	0.98	0.973	0.983	0.933	0.979	0.03297	0.183
26	3200	203	1	on	conv.	2	0.803	0.78	0.757	0.75	0.767	0.743	0.83	0.803	0.779	0.03052	2.162
27	2700	330	1	off	climb.	2	1.05	1.033	1.073	1.01	0.98	1.073	1.03	1.06	1.039	0.03232	-0.333
28	3200	330	1	on	climb.	2	0.913	0.883	0.89	0.89	1.023	1.023	1.003	0.987	0.952	0.06311	0.415
29	3200	203	1	on	climb.	1	0.977	1.087	1.077	1.14	1.06	1.083	1.087	1.14	1.081	0.05114	-0.688
30	2700	203	0.5	off	conv.	2	7.533	6.4	7.9	5.3	1.67	6.233	7	11.167	6.65	2.66531	-17.028
31	2700	330	1	on	climb.	2	1.1	1.11	0.963	1.04	1.023	1.017	0.983	1.003	1.03	0.05216	-0.265
32	3200	330	0.5	off	climb.	2	1.217	1.13	1.147	1.155	1.3	1.183	1.247	1.13	1.189	0.06140	-1.511
33	2700	330	1	off	conv.	2	N.A.	32.5	N.A.	N.A.	15.2	16.2	36.7	27.2	25.56	9.61629	-28.617
34	3200	330	1	off	conv.	2	N.A.	30.7	N.A.	33	N.A.	15.5	15.2	N.A.	23.6	9.57323	-27.964
35	3200	330	0.5	on	climb.	2	1.14	1.117	1.09	1.073	1.117	1.097	1.157	1.057	1.106	0.03344	-0.879
36	3200	330	0.5	off	conv.	1	1.43	1.553	1.05	1.197	1.45	1.303	1.173	1.707	1.358	0.21762	-2.754
37	3200	330	1	off	climb.	1	1.1	1.033	1.017	1.007	1.017	1.053	1	1.09	1.04	0.03792	-0.343
38	3200	203	1	off	conv.	1	2.507	2.23	2.08	3.933	2.08	3.013	5.1	5.1	3.255	1.29271	-10.813
39	3200	330	1	off	climb.	2	1.067	1.147	1.107	1.123	1.097	1.04	1.05	0.963	1.074	0.05788	-0.633
40	3200	203	0.5	off	conv.	2	22	N.A.	15.2	11.7	15	12.5	16.5	8.2	14.44	4.33007	-23.515
41	3200	330	1	off	conv.	1	1.69	1.597	1.68	2.23	4.407	2.657	3.6	5.033	2.862	1.33402	-9.889
42	3200	330	0.5	on	conv.	1	1.117	0.847	0.897	0.797	0.767	0.773	0.783	0.84	0.853	0.11568	1.315
43	3200	330	0.5	off	climb.	1	1.02	1.007	1.007	0.953	0.997	0.99	1.013	1.003	0.999	0.02064	0.009
44	3200	203	0.5	off	climb.	1	0.937	0.96	0.953	0.873	1.017	0.927	0.937	0.91	0.939	0.04152	0.537

Appendix B1. Full factorial data set for perpendicular measurement method.....continued

Run	TS	WS	DC	C	DIC	CL	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	SNR
45	3200	203	1	on	conv.	1	1.04	1.157	1.097	1.03	0.913	0.94	0.94	0.987	1.013	0.08464	-0.139
46	3200	330	1	on	climb.	1	0.94	1.04	1.023	1.03	0.897	0.873	0.913	0.98	0.962	0.06523	0.319
47	3200	203	0.5	on	climb.	2	0.973	0.957	0.93	0.95	0.957	0.923	1.023	1.107	0.978	0.06057	0.183
48	2700	330	0.5	on	conv.	1	1.013	1.09	1.117	1.14	1.13	1.217	1.13	1.07	1.113	0.05918	-0.944
49	2700	330	0.5	off	conv.	1	1.447	1.34	1.523	1.29	1.44	1.503	1.423	1.42	1.423	0.07732	-3.077
50	3200	330	1	on	conv.	1	0.84	0.853	0.863	0.863	0.823	0.783	0.79	0.817	0.829	0.03123	1.624
51	2700	203	1	off	climb.	2	0.89	0.82	0.91	0.97	0.92	0.86	1.16	1.05	0.948	0.11055	0.417
52	3200	330	0.5	on	conv.	2	0.99	1.11	1.1	1.13	0.95	0.94	1.01	0.96	1.024	0.07782	-0.226
53	2700	330	0.5	off	climb.	1	1.09	1.02	0.97	1.05	1.05	1.07	1.02	1.05	1.04	0.03665	-0.345
54	3200	203	0.5	on	conv.	1	0.89	0.85	0.85	0.85	0.86	0.93	0.87	0.81	0.864	0.03503	1.266
55	2700	330	0.5	on	climb.	1	1.09	1	1.03	1.06	1.05	1.03	1.04	1.05	1.044	0.02615	-0.374
56	3200	203	1	off	conv.	2	26.07	18.97	19.6	18.7	25.3	16.5	18.63	26.53	21.29	3.98842	-26.694
57	3200	330	0.5	on	climb.	1	0.96	1	1.01	1	1.01	0.94	0.91	0.95	0.973	0.03770	0.237
58	2700	330	1	on	climb.	1	0.89	0.85	0.8	0.88	0.9	0.89	0.86	0.88	0.869	0.03227	1.217
59	3200	203	0.5	off	climb.	2	1.39	1.57	1.6	1.12	1.03	1.24	1.55	1.24	1.343	0.21763	-2.657
60	2700	203	1	off	conv.	2	11.73	7.56	10.4	12.07	24.87	12.87	18.75	N.A.	14.04	5.84948	-23.547
61	3200	330	0.5	off	conv.	2	16.87	8.73	11.07	14.83	16.4	19.36	13.47	14.97	14.46	3.36545	-23.406
62	2700	203	0.5	on	climb.	2	1.24	1.14	1.09	1.15	1.12	1.11	1.06	1.11	1.128	0.05339	-1.051
63	2700	203	1	on	conv.	1	1.09	1.05	0.95	0.94	1.1	1.12	1.06	1.12	1.054	0.07170	-0.472
64	2700	330	1	off	conv.	1	3.08	3.53	4.03	4.4	3.97	4	3.67	5.83	4.064	0.81542	-12.329

Appendix B1. Continuation……full factorial data set for perpendicular measurement method.

APPENDIX B2

TAGUCHI L_{16} DATA SETS FOR PERPENDICULAR MEASUREMENT METHOD FEATURING SURFACE ROUGHNESS RESPONSE

Abbreviations

Run – run number.
FF run equiv. – Equivalent run in the full factorial

Factors:
TS - Tool speed (rev/min).
WS – Workpiece Travelling speed (mm/min).
DC – Depth of cut (mm).
C – Coolant.
DIC – Direction of Cut.
  Climb – Climbing milling
  Conv. – conventional milling.
CL – Number of Cuts.
Error – error terms.

Repetitions:
R1 – Repetition One.
R2 – Repetition Two.
R3 – Repetition Three.
R4 – Repetition Four.
R5 – Repetition Five.
R6 – Repetition Six.
R7 – Repetition Seven.
R8 – Repetition Eight.

Responses (Stats calculated for each run only):
Mean – Mean.
STD – Standard Deviation.
SNR – Signal-to-Noise Ratio.

Notes:
N.A. – Data Not Available.
In all cases the non-availability of the data was due to extreme values (high) of surface roughness, so the tester (Mitutoyo, 1989) was unable to report any measurement. N.A. measures were treated as missing values and therefore ignored for purposes of calculating statistics. This means that metrics (responses) were calculated considering only those repetitions with non-missing value

- **A*B** represents the interaction between factors **A** and **B**.
- Linear graphs II and IV as Taguchi's notation (from Peace, 1993).

run	FF run equiv.	C	DIC	C*DIC	CL	C*CL	DIC*CL	WS*E	WS	C*WS	TS	C*TS	DC	C*DC	C*Error	Error	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	SNR
1	21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1.08	1.063	0.907	0.93	1.017	1.02	0.947	0.94	0.988	0.0653	0.088
2	53	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1.09	1.02	0.97	1.05	1.05	1.07	1.02	1.05	1.040	0.0366	-0.345
3	59	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1.39	1.57	1.6	1.12	1.03	1.24	1.55	1.24	1.343	0.2176	-2.657
4	27	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1.05	1.033	1.073	1.01	0.98	1.073	1.03	1.06	1.039	0.0323	-0.333
5	2	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	2.003	2.03	2.49	4.457	3.44	3.007	2.473	4.517	3.052	1.0049	-10.086
6	36	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1.43	1.553	1.05	1.197	1.45	1.303	1.173	1.707	1.358	0.2176	-2.754
7	30	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	7.533	6.4	7.9	5.3	1.67	6.233	7	11.167	6.650	2.6653	-17.028
8	34	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	N.A.	30.7	N.A.	33	N.A.	15.5	15.2	N.A.	23.600	9.5732	-27.964
9	29	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	0.977	1.087	1.077	1.14	1.06	1.083	1.087	1.14	1.081	0.0511	-0.688
10	55	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	1.09	1	1.03	1.06	1.05	1.03	1.04	1.05	1.044	0.0262	-0.374
11	47	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	0.973	0.957	0.93	0.95	0.957	0.923	1.023	1.107	0.978	0.0606	0.183
12	31	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	1.1	1.11	0.963	1.04	1.023	1.017	0.983	1.003	1.030	0.0522	-0.265
13	63	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1.09	1.05	0.95	0.94	1.1	1.12	1.06	1.12	1.054	0.0717	-0.472
14	42	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	1.117	0.847	0.897	0.797	0.767	0.773	0.783	0.84	0.853	0.1157	1.315
15	11	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	0.957	0.913	0.897	0.93	0.897	0.887	0.903	0.92	0.913	0.0226	0.788
16	10	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	0.947	0.923	0.967	0.887	0.87	0.907	0.93	0.897	0.916	0.0321	0.757

Appendix B2. Taguchi data set for perpendicular measurement method, using Linear Graph II.

run	FF run equiv.	C	TS	C*TS	WS	C*WS	DC	C*DC	DIC	C*DIC	CL	C*CL	Error	C*T	ERR	C*ERR	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	SNR
1	21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1.08	1.063	0.907	0.93	1.017	1.02	0.947	0.94	0.988	0.065	0.088
2	56	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	26.07	18.97	19.6	18.7	25.3	16.5	18.63	26.53	21.29	3.988	-26.694
3	43	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1.02	1.007	1.007	0.953	0.997	0.99	1.013	1.003	0.999	0.021	0.009
4	61	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	16.87	8.73	11.07	14.83	16.4	19.36	13.47	14.97	14.46	3.365	-23.406
5	7	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1.073	1.003	1.073	1.087	1.09	1.09	1.073	1.047	1.067	0.029	-0.566
6	14	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1.207	1.547	1.41	2.013	1.49	2.15	1.367	1.637	1.603	0.324	-4.249
7	27	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1.05	1.033	1.073	1.01	0.98	1.073	1.03	1.06	1.039	0.032	-0.333
8	64	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	3.08	3.53	4.03	4.4	3.97	4	3.67	5.83	4.064	0.815	-12.329
9	29	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	0.977	1.087	1.077	1.14	1.06	1.083	1.087	1.14	1.081	0.051	-0.688
10	26	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	0.803	0.78	0.757	0.75	0.767	0.743	0.83	0.803	0.779	0.031	2.162
11	57	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	0.96	1	1.01	1	1.01	0.94	0.91	0.95	0.973	0.038	0.237
12	52	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	0.99	1.11	1.1	1.13	0.95	0.94	1.01	0.96	1.024	0.078	-0.226
13	62	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1.24	1.14	1.09	1.15	1.12	1.11	1.06	1.11	1.128	0.053	-1.051
14	12	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	0.907	0.907	0.883	0.823	0.837	0.873	0.89	0.867	0.873	0.031	1.171
15	31	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1.1	1.11	0.963	1.04	1.023	1.017	0.983	1.003	1.03	0.052	-0.265
16	5	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	0.933	0.907	0.913	0.913	0.88	0.923	0.89	0.897	0.907	0.017	0.846

Appendix B2. Taguchi data set for perpendicular measurement method, using Linear Graph IV

APPENDIX B3

FULL FACTORIAL DATA SET FOR PARALLEL MEASUREMENT METHOD FEATURING SURFACE ROUGHNESS RESPONSE

(N.B. Abbreviations as in Appendix B1)

Run	TS	WS	DC	C	DIC	CL	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	SNR
1	2700	330	1.0	off	climb.	1	0.3700	0.3370	0.3200	0.3870	0.2270	0.2070	0.1830	0.1830	0.2768	0.0856	10.8093
2	2700	203	1.0	off	conv.	1	0.9730	1.3700	3.0900	2.7830	1.1070	1.5800	1.9630	2.7730	1.9549	0.8289	-6.4569
3	2700	203	1.0	on	climb.	2	0.1470	0.1970	0.1970	0.1830	0.2100	0.1430	0.1630	0.2230	0.1829	0.0293	14.6603
4	2700	203	0.5	off	climb.	1	0.4370	0.3800	0.3630	0.4070	0.1470	0.1070	0.1200	0.1830	0.2680	0.1410	10.4955
5	2700	330	1.0	on	conv.	1	0.3670	0.4230	0.3570	0.3030	0.3100	0.2600	0.2700	0.2630	0.3191	0.0585	9.7951
6	3200	203	1.0	off	climb.	2	0.1330	0.1370	0.1830	0.1930	0.4670	0.3930	0.4200	0.4370	0.2954	0.1460	9.7515
7	2700	203	0.5	off	climb.	2	0.1330	0.1430	0.1570	0.1600	0.1700	0.1900	0.1700	0.1800	0.1629	0.0188	15.7128
8	2700	330	0.5	off	climb.	2	0.1430	0.1800	0.1670	0.1630	0.2130	0.1930	0.2330	0.2000	0.1865	0.0292	14.4944
9	2700	203	1.0	on	conv.	2	0.4270	0.4230	0.4070	0.3700	0.2170	0.2300	0.2800	0.2370	0.3239	0.0920	9.4964
10	3200	330	1.0	on	conv.	2	0.3230	0.2630	0.3100	0.2730	0.2470	0.2230	0.3670	0.2430	0.2811	0.0483	10.9111
11	2700	203	0.5	on	conv.	2	0.2670	0.2230	0.2630	0.3000	0.2300	0.2200	0.2500	0.2400	0.2491	0.0269	12.0274
12	2700	203	0.5	on	conv.	1	0.3200	0.3370	0.2870	0.3370	0.2770	0.2400	0.2270	0.2470	0.2840	0.0440	10.8435
13	2700	330	0.5	on	conv.	2	0.4930	0.4570	0.4500	0.3470	0.2100	0.2330	0.3100	0.2870	0.3484	0.1074	8.8121
14	2700	203	0.5	off	conv.	1	1.1330	0.7270	0.7000	0.8430	1.0230	0.9500	1.3070	1.0270	0.9638	0.2051	0.1520
15	3200	203	1.0	on	climb.	2	0.4900	0.4270	0.4170	0.4470	0.5830	0.4900	0.5200	0.4600	0.4793	0.0543	6.3402
16	3200	203	0.5	on	conv.	2	0.1870	0.2270	0.1530	0.2600	0.2200	0.2200	0.1570	0.1800	0.2005	0.0373	13.8280
17	2700	203	1.0	off	climb.	1	0.1630	0.1530	0.1330	0.1570	0.1130	0.1330	0.1270	0.1400	0.1399	0.0168	17.0305
18	3200	203	0.5	off	conv.	1	1.3130	1.4830	1.0730	0.6800	2.0400	1.8400	1.9830	0.8900	1.4128	0.5129	-3.4754
19	2700	330	0.5	on	climb.	2	0.1770	0.1870	0.1930	0.2500	0.3800	0.3500	0.2930	0.3270	0.2696	0.0794	11.0671
20	3200	203	0.5	on	climb.	1	0.3370	0.2800	0.3200	0.3930	0.3430	0.4330	0.4630	0.4430	0.3765	0.0661	8.3692
21	3200	203	1.0	off	climb.	1	0.3030	0.2630	0.2700	0.2100	0.3530	0.3600	0.4100	0.4070	0.3220	0.0722	9.6560

Appendix B3. Full factorial data set for parallel measurement method. .....continued

Run	TS	WS	DC	C	DIC	CL	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	SNR
22	2700	330	1.0	on	conv.	2	0.4200	0.3530	0.3330	0.2970	0.2230	0.2500	0.3070	0.3100	0.3116	0.0607	9.9854
23	2700	203	0.5	on	climb.	1	0.3370	0.3030	0.2770	0.2830	0.1370	0.1670	0.1570	0.1400	0.2251	0.0825	12.4689
24	2700	330	0.5	off	conv.	2	4.8300	7.2000	8.8000	4.6300	8.1300	6.6700	8.5700	2.7000	6.4413	2.1860	-16.5964
25	2700	203	1.0	on	climb.	1	0.2530	0.2830	0.2270	0.2700	0.3630	0.3770	0.3170	0.4000	0.3113	0.0631	9.9842
26	3200	203	1.0	on	conv.	2	0.3170	0.3300	0.3500	0.3170	0.2430	0.4430	0.2800	0.2900	0.3213	0.0592	9.7358
27	2700	330	1.0	off	climb.	2	0.2970	0.2100	0.2170	0.2730	0.4600	0.3900	0.4230	0.3870	0.3321	0.0955	9.2705
28	3200	330	1.0	on	climb.	2	0.1610	0.1540	0.1390	0.1930	0.2300	0.2120	0.1700	0.1860	0.1806	0.0306	14.7569
29	3200	203	1.0	on	climb.	1	0.1670	0.1610	0.1590	0.1910	0.4610	0.3800	0.4570	0.4070	0.2979	0.1400	9.7521
30	2700	203	0.5	off	conv.	2	7.9000	4.5300	6.7670	4.0330	6.4330	5.6670	5.9670	10.0330	6.4163	1.9051	-16.4684
31	2700	330	1.0	on	climb.	2	0.3500	0.3130	0.3030	0.3100	0.5030	0.5070	0.4500	0.4200	0.3945	0.0864	7.9004
32	3200	330	0.5	off	climb.	2	0.3670	0.3770	0.4470	0.4730	0.2700	0.2300	0.2100	0.2030	0.3221	0.1078	9.4335
33	2700	330	1.0	off	conv.	2	31.0000	N.A.	N.A.	N.A.	N.A.	32.7000	N.A.	N.A.	31.8500	1.2021	-30.0653
34	3200	330	1.0	off	conv.	2	24.7000	N.A.	N.A.	N.A.	19.2000	N.A.	10.5000	19.5000	18.4750	5.8858	-25.6503
35	3200	330	0.5	on	climb.	2	0.1900	0.2000	0.1730	0.1670	0.1630	0.1700	0.1670	0.1700	0.1750	0.0130	15.1184
36	3200	330	0.5	off	conv.	1	1.4400	1.1070	0.9400	0.9900	0.8130	0.9870	0.7730	0.7400	0.9738	0.2260	0.0310
37	3200	330	1.0	off	climb.	1	0.2130	0.2400	0.2570	0.2530	0.3200	0.3400	0.3030	0.3300	0.2820	0.0471	10.8902
38	3200	203	1.0	off	conv.	1	1.0570	1.0700	1.3800	1.7830	1.7070	2.3400	3.6000	4.7670	2.2130	1.3224	-8.0804
39	3200	330	1.0	off	climb.	2	0.2600	0.2800	0.2570	0.2730	0.2830	0.2800	0.2100	0.3270	0.2713	0.0327	11.2777
40	3200	203	0.5	off	conv.	2	17.4000	14.5700	16.0700	14.8000	12.5700	11.9700	15.1300	13.0000	14.4388	1.8405	-23.2519
41	3200	330	1.0	off	conv.	1	1.5167	1.2130	1.2630	1.2970	2.7670	2.1570	2.9670	2.4730	1.9567	0.7218	-6.3191
42	3200	330	0.5	on	conv.	1	0.6300	0.3800	0.3470	0.2630	0.3500	0.3070	0.3130	0.3170	0.3634	0.1132	8.4387

Appendix B3. Full factorial data set for parallel measurement method. .....continued

Run	TS	WS	DC	C	DIC	CL	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	SNR
43	3200	330	0.5	off	climb.	1	0.3300	0.3300	0.3470	0.2900	0.2370	0.2130	0.2300	0.2130	0.2738	0.0568	11.0922
44	3200	203	0.5	off	climb.	1	0.3570	0.3100	0.3230	0.2800	0.1730	0.1670	0.1770	0.1570	0.2430	0.0825	11.8702
45	3200	203	1.0	on	conv.	1	0.6800	0.7230	0.5570	0.5230	0.8200	0.2570	0.2400	0.3400	0.5175	0.2198	5.0854
46	3200	330	1.0	on	climb.	1	0.2170	0.1900	0.2030	0.2200	0.2130	0.3470	0.1900	0.2300	0.2263	0.0508	12.7208
47	3200	203	0.5	on	climb.	2	0.2630	0.2630	0.2500	0.2800	0.2300	0.2070	0.2470	0.2730	0.2516	0.0239	11.9507
48	2700	330	0.5	on	conv.	1	0.3830	0.4230	0.3230	0.4300	0.4630	0.3230	0.5730	0.5460	0.4330	0.0926	7.0997
49	2700	330	0.5	off	conv.	1	1.1130	1.4170	2.3230	1.2400	1.2400	1.5970	1.2000	1.4970	1.4534	0.3875	-3.5096
50	3200	330	1.0	on	conv.	1	0.5700	0.6370	0.5400	0.8470	0.3070	0.3630	0.3130	0.4230	0.5000	0.1862	5.5234
51	2700	203	1.0	off	climb.	2	0.5950	0.5450	0.5000	0.5100	0.5130	0.7400	0.2900	0.2400	0.4916	0.1604	5.7806
52	3200	330	0.5	on	conv.	2	0.4200	0.4400	0.4070	0.3230	0.2400	0.2500	0.3630	0.3070	0.3438	0.0763	9.0917
53	2700	330	0.5	off	climb.	1	0.4400	0.4000	0.3730	0.3700	0.2170	0.1830	0.2470	0.2370	0.3084	0.0976	9.8538
54	3200	203	0.5	on	conv.	1	0.2900	0.3530	0.2570	0.2570	0.4130	0.4070	0.4300	0.3730	0.3475	0.0707	9.0263
55	2700	330	0.5	on	climb.	1	0.5300	0.4300	0.5000	0.4830	0.4300	0.3170	0.3070	0.3900	0.4234	0.0818	7.3259
56	3200	203	1.0	off	conv.	2	27.7000	21.7000	9.7000	24.2000	17.2000	N.A.	23.2000	N.A.	20.6167	6.3515	-26.6150
57	3200	330	0.5	on	climb.	1	0.4630	0.3130	0.3330	0.3030	0.2170	0.3170	0.2900	0.2730	0.3136	0.0701	9.8862
58	2700	330	1.0	on	climb.	1	0.4300	0.4070	0.4400	0.4530	0.3470	0.3300	0.2570	0.2300	0.3618	0.0851	8.6264
59	3200	203	0.5	off	climb.	2	0.2570	0.3170	0.3230	0.4970	0.5970	0.4900	0.5230	0.5500	0.4443	0.1262	6.7510
60	2700	203	1.0	off	conv.	2	18.5000	12.5000	13.5000	15.2000	26.5000	N.A.	19.7000	N.A.	17.6500	5.1574	-25.2334
61	3200	330	0.5	off	conv.	2	N.A.	12.7000	13.5000	19.5000	16.2000	15.5000	21.2000	21.0000	17.0857	3.4993	-24.8061
62	2700	203	0.5	on	climb.	2	0.2830	0.3130	0.2970	0.2900	0.2970	0.3370	0.3800	0.3170	0.3143	0.0316	10.0161
63	2700	203	1.0	on	conv.	1	0.6570	0.6630	0.6230	0.6970	0.7800	0.7170	0.4570	0.5870	0.6476	0.0969	3.6893
64	2700	330	1.0	off	conv.	1	4.0000	1.8300	1.9700	2.1000	1.4670	4.4000	2.0300	1.9000	2.4621	1.0946	-8.5189

Appendix B3. Continuation......full factorial data set for parallel measurement method.

APPENDIX B4

TAGUCHI L_{16} DATA SETS FOR PARALLEL MEASUREMENT METHOD FEATURING SURFACE ROUGHNESS RESPONSE

(N.B. Abbreviations as in Appendix B2)

run	FF run equiv.	C	DIC	C*DIC	CL	C*CL	DIC*CL	WS*E	WS	C*WS	TS	C*TS	DC	C*DC	C*Error	Error	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	STB
1	21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.303	0.263	0.270	0.210	0.353	0.360	0.410	0.407	0.322	0.072	9.656
2	53	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	0.440	0.400	0.373	0.370	0.217	0.183	0.247	0.237	0.308	0.098	9.854
3	59	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	0.257	0.317	0.323	0.497	0.597	0.490	0.523	0.550	0.444	0.126	6.751
4	27	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	0.297	0.210	0.217	0.273	0.460	0.390	0.423	0.387	0.332	0.096	9.270
5	2	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	0.973	1.370	3.090	2.783	1.107	1.580	1.963	2.773	1.955	0.829	-6.457
6	36	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1.440	1.107	0.940	0.990	0.813	0.987	0.773	0.740	0.974	0.226	0.031
7	30	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	7.900	4.530	6.767	4.033	6.433	5.667	5.967	10.033	6.416	1.905	-16.468
8	34	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	24.700	N.A.	N.A.	N.A.	19.200	N.A.	10.500	19.500	18.475	5.886	-25.650
9	29	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	0.167	0.161	0.159	0.191	0.461	0.380	0.457	0.407	0.298	0.140	9.752
10	55	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	0.530	0.430	0.500	0.483	0.430	0.317	0.307	0.390	0.423	0.082	7.326
11	47	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	0.263	0.263	0.250	0.280	0.230	0.207	0.247	0.273	0.252	0.024	11.951
12	31	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	0.350	0.313	0.303	0.310	0.503	0.507	0.450	0.420	0.395	0.086	7.900
13	63	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	0.657	0.663	0.623	0.697	0.780	0.717	0.457	0.587	0.648	0.097	3.689
14	42	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	0.630	0.380	0.347	0.263	0.350	0.307	0.313	0.317	0.363	0.113	8.439
15	11	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	0.267	0.223	0.263	0.300	0.230	0.220	0.250	0.240	0.249	0.027	12.027
16	10	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	0.323	0.263	0.310	0.273	0.247	0.223	0.367	0.243	0.281	0.048	10.911

Appendix B4. Taguchi data set for parallel measurement method, using Linear Graph II.

run	FF run equiv.	C	TS	C*TS	WS	C*WS	DC	C*DC	DIC	C*DIC	CL	C*CL	Error	C*T	ERR	C*ERR	R1	R2	R3	R4	R5	R6	R7	R8	Mean	STD	STB
1	21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.303	0.263	0.270	0.210	0.353	0.360	0.410	0.407	0.322	0.072	9.656
2	56	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	27.700	21.700	9.700	24.200	17.200	N.A.	23.200	N.A.	20.617	6.352	-26.615
3	43	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	0.330	0.330	0.347	0.290	0.237	0.213	0.230	0.213	0.274	0.057	11.092
4	61	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	N.A.	12.700	13.500	19.500	16.200	15.500	21.200	21.000	17.086	3.499	-24.806
5	7	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	0.1330	0.1430	0.1570	0.1600	0.1700	0.1900	0.1700	0.1800	0.1629	0.0188	15.7128
6	14	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1.1330	0.7270	0.7000	0.8430	1.0230	0.9500	1.3070	1.0270	0.9638	0.2051	0.1520
7	27	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	0.2970	0.2100	0.2170	0.2730	0.4600	0.3900	0.4230	0.3870	0.3321	0.0955	9.2705
8	64	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	4.0000	1.8300	1.9700	2.1000	1.4670	4.4000	2.0300	1.9000	2.4621	1.0946	-8.5189
9	29	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	0.1670	0.1610	0.1590	0.1910	0.4610	0.3800	0.4570	0.4070	0.2979	0.1400	9.7521
10	26	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	0.3170	0.3300	0.3500	0.3170	0.2430	0.4430	0.2800	0.2900	0.3213	0.0592	9.7358
11	57	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	0.4630	0.3130	0.3330	0.3030	0.2170	0.3170	0.2900	0.2730	0.3136	0.0701	9.8862
12	52	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	0.4200	0.4400	0.4070	0.3230	0.2400	0.2500	0.3630	0.3070	0.3438	0.0763	9.0917
13	62	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	0.2830	0.3130	0.2970	0.2900	0.2970	0.3370	0.3800	0.3170	0.3143	0.0316	10.0161
14	12	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	0.3200	0.3370	0.2870	0.3370	0.2770	0.2400	0.2270	0.2470	0.2840	0.0440	10.8435
15	31	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	0.3500	0.3130	0.3030	0.3100	0.5030	0.5070	0.4500	0.4200	0.3945	0.0864	7.9004
16	5	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	0.3670	0.4230	0.3570	0.3030	0.3100	0.2600	0.2700	0.2630	0.3191	0.0585	9.7951

Appendix B4. Taguchi data set for parallel measurement method, using Linear Graph IV.

APPENDIX B5

FULL FACTORIAL DATA SET FOR PERPENDICULAR MEASUREMENT METHOD FEATURING SURFACE ROUGHNESS RESPONSE (FULL MILLING DATA SET)

(N.B. Abbreviations as in Appendix B1)

(N.B.2. This data set combines both milling blocks: the first block from runs 1 to 64 (Appendix B1) and the second block from runs 65 to 128)

OBS	TS	WS	DC	C	DIC	CL	Tool	R1	R2	R3	R4	Mean	STD	STB
1	2700	330	1	off	climb.	1	4-flute	1.273	1.23	1.263	1.247	1.2533	0.01884	-1.961
2	2700	203	1	off	conv.	1	4-flute	2.003	2.03	2.49	4.457	2.745	1.16301	-9.319
3	2700	203	1	on	climb.	2	4-flute	1.003	0.97	0.973	0.967	0.9783	0.01668	0.1901
4	2700	203	0.5	off	climb.	1	4-flute	1.053	1.03	1.057	1.063	1.0508	0.01443	-0.431
5	2700	330	1	on	conv.	1	4-flute	0.933	0.907	0.913	0.913	0.9165	0.01136	0.7569
6	3200	203	1	off	climb.	2	4-flute	1.223	1.19	1.18	1.177	1.1925	0.02108	-1.53
7	2700	203	0.5	off	climb.	2	4-flute	1.073	1.003	1.073	1.087	1.059	0.03791	-0.502
8	2700	330	0.5	off	climb.	2	4-flute	1.203	1.118	1.19	1.257	1.192	0.05723	-1.533
9	2700	203	1	on	conv.	2	4-flute	0.99	0.947	0.967	0.98	0.971	0.01857	0.2544
10	3200	330	1	on	conv.	2	4-flute	0.947	0.923	0.967	0.887	0.931	0.03441	0.6166
11	2700	203	0.5	on	conv.	2	4-flute	0.957	0.913	0.897	0.93	0.9243	0.02566	0.6817
12	2700	203	0.5	on	conv.	1	4-flute	0.907	0.907	0.883	0.823	0.88	0.03965	1.1037
13	2700	330	0.5	on	conv.	2	4-flute	0.93	0.93	0.97	0.94	0.9425	0.01893	0.5131
14	2700	203	0.5	off	conv.	1	4-flute	1.207	1.547	1.41	2.013	1.5443	0.34229	-3.932
15	3200	203	1	on	climb.	2	4-flute	1.023	1.03	1.03	1.13	1.0533	0.05127	-0.458
16	3200	203	0.5	on	conv.	2	4-flute	0.78	0.78	0.863	0.897	0.83	0.05938	1.6018
17	2700	203	1	off	climb.	1	4-flute	1.037	0.963	1.003	0.99	0.9983	0.03074	0.0121
18	3200	203	0.5	off	conv.	1	4-flute	1.47	1.407	1.33	1.147	1.3385	0.13992	-2.568
19	2700	330	0.5	on	climb.	2	4-flute	1.29	1.22	1.27	1.157	1.2343	0.05932	-1.836
20	3200	203	0.5	on	climb.	1	4-flute	1.113	1.063	0.973	0.983	1.033	0.06683	-0.296
21	3200	203	1	off	climb.	1	4-flute	1.08	1.063	0.907	0.93	0.995	0.0891	0.0175
22	2700	330	1	on	conv.	2	4-flute	0.907	0.893	0.84	0.97	0.9025	0.05346	0.8796

Appendix B5. Full factorial data set for perpendicular measurement method (Full milling data set)……continued

OBS	TS	WS	DC	C	DIC	CL	Tool	R1	R2	R3	R4	Mean	STD	STB
23	2700	203	0.5	on	climb.	1	4-flute	1.063	0.99	0.973	0.94	0.9915	0.05199	0.0652
24	2700	330	0.5	off	conv.	2	4-flute	4	6.7	8	2.7	5.35	2.42831	-15.19
25	2700	203	1	on	climb.	1	4-flute	0.953	0.957	1.03	1.02	0.99	0.04065	0.0818
26	3200	203	1	on	conv.	2	4-flute	0.803	0.78	0.757	0.75	0.7725	0.02403	2.2389
27	2700	330	1	off	climb.	2	4-flute	1.05	1.033	1.073	1.01	1.0415	0.02664	-0.355
28	3200	330	1	on	climb.	2	4-flute	0.913	0.883	0.89	0.89	0.894	0.01309	0.9726
29	3200	203	1	on	climb.	1	4-flute	0.977	1.087	1.077	1.14	1.0703	0.06804	-0.603
30	2700	203	0.5	off	conv.	2	4-flute	7.533	6.4	7.9	5.3	6.7833	1.17703	-16.73
31	2700	330	1	on	climb.	2	4-flute	1.1	1.11	0.963	1.04	1.0533	0.06764	-0.464
32	3200	330	0.5	off	climb.	2	4-flute	1.217	1.13	1.147	1.155	1.1623	0.03796	-1.309
33	2700	330	1	off	conv.	2	4-flute	N.A.	32.5	N.A.	N.A.	32.5	0	-30.24
34	3200	330	1	off	conv.	2	4-flute	N.A.	30.7	N.A.	33	31.85	1.62635	-30.07
35	3200	330	0.5	on	climb.	2	4-flute	1.14	1.117	1.09	1.073	1.105	0.02954	-0.87
36	3200	330	0.5	off	conv.	1	4-flute	1.43	1.553	1.05	1.197	1.3075	0.22642	-2.425
37	3200	330	1	off	climb.	1	4-flute	1.1	1.033	1.017	1.007	1.0393	0.04189	-0.34
38	3200	203	1	off	conv.	1	4-flute	2.507	2.23	2.08	3.933	2.6875	0.84896	-8.9
39	3200	330	1	off	climb.	2	4-flute	1.067	1.147	1.107	1.123	1.111	0.03363	-0.917
40	3200	203	0.5	off	conv.	2	4-flute	22	N.A.	15.2	11.7	16.3	5.23737	-24.53
41	3200	330	1	off	conv.	1	4-flute	1.69	1.597	1.68	2.23	1.7993	0.29018	-5.186
42	3200	330	0.5	on	conv.	1	4-flute	1.117	0.847	0.897	0.797	0.9145	0.14104	0.6995
43	3200	330	0.5	off	climb.	1	4-flute	1.02	1.007	1.007	0.953	0.9968	0.0298	0.0254
44	3200	203	0.5	off	climb.	1	4-flute	0.937	0.96	0.953	0.873	0.9308	0.03969	0.6174

Appendix B5. Full factorial data set for perpendicular measurement method (Full milling data set) ......continued

OBS	TS	WS	DC	C	DIC	CL	Tool	R1	R2	R3	R4	Mean	STD	STB
45	3200	203	1	on	conv.	1	4-flute	1.04	1.157	1.097	1.03	1.081	0.05863	-0.686
46	3200	330	1	on	climb.	1	4-flute	0.94	1.04	1.023	1.03	1.0083	0.04603	-0.078
47	3200	203	0.5	on	climb.	2	4-flute	0.973	0.957	0.93	0.95	0.9525	0.01782	0.4216
48	2700	330	0.5	on	conv.	1	4-flute	1.013	1.09	1.117	1.14	1.09	0.05525	-0.757
49	2700	330	0.5	off	conv.	1	4-flute	1.447	1.34	1.523	1.29	1.4	0.10494	-2.941
50	3200	330	1	on	conv.	1	4-flute	0.84	0.853	0.863	0.863	0.8548	0.0109	1.3627
51	2700	203	1	off	climb.	2	4-flute	0.89	0.82	0.91	0.97	0.8975	0.06185	0.9239
52	3200	330	0.5	on	conv.	2	4-flute	0.99	1.11	1.1	1.13	1.0825	0.06292	-0.7
53	2700	330	0.5	off	climb.	1	4-flute	1.09	1.02	0.97	1.05	1.0325	0.05058	-0.286
54	3200	203	0.5	on	conv.	1	4-flute	0.89	0.85	0.85	0.85	0.86	0.02	1.3083
55	2700	330	0.5	on	climb.	1	4-flute	1.09	1	1.03	1.06	1.045	0.03873	-0.387
56	3200	203	1	off	conv.	2	4-flute	26.07	18.97	19.6	18.7	20.835	3.51031	-26.47
57	3200	330	0.5	on	climb.	1	4-flute	0.96	1	1.01	1	0.9925	0.02217	0.0638
58	2700	330	1	on	climb.	1	4-flute	0.89	0.85	0.8	0.88	0.855	0.04041	1.3534
59	3200	203	0.5	off	climb.	2	4-flute	1.39	1.57	1.6	1.12	1.42	0.22045	-3.124
60	2700	203	1	off	conv.	2	4-flute	11.73	7.56	10.4	12.07	10.44	2.05077	-20.5
61	3200	330	0.5	off	conv.	2	4-flute	16.87	8.73	11.07	14.83	12.875	3.66156	-22.45
62	2700	203	0.5	on	climb.	2	4-flute	1.24	1.14	1.09	1.15	1.155	0.06245	-1.261
63	2700	203	1	on	conv.	1	4-flute	1.09	1.05	0.95	0.94	1.0075	0.07411	-0.082
64	2700	330	1	off	conv.	1	4-flute	3.08	3.53	4.03	4.4	3.76	0.57671	-11.58
65	3200	203	1	on	conv	1	2-flute	1.275	1.250	1.200	1.220	1.2363	0.03301	-1.844
66	2700	330	0.5	on	conv	1	2-flute	1.275	1.220	1.210	1.200	1.2263	0.03351	-1.774

Appendix B5. Full factorial data set for perpendicular measurement method (Full milling data set). ……continued

OBS	TS	WS	DC	C	DIC	CL	Tool	R1	R2	R3	R4	Mean	STD	STB
67	3200	330	1	on	climb	2	2-flute	0.835	0.850	0.860	0.860	0.8513	0.01181	1.3982
68	3200	203	1	off	climb	1	2-flute	0.950	1.010	1.085	1.035	1.02	0.05612	-0.182
69	3200	203	0.5	on	climb	2	2-flute	1.110	1.150	1.170	1.235	1.1663	0.05218	-1.342
70	2700	330	1	off	climb	1	2-flute	0.985	1.095	1.100	1.150	1.0825	0.06958	-0.702
71	3200	330	1	off	conv	1	2-flute	1.210	1.300	1.195	1.260	1.2413	0.04802	-1.882
72	3200	330	0.5	off	conv	1	2-flute	1.370	1.220	1.335	1.435	1.34	0.09009	-2.557
73	2700	203	0.5	on	conv	1	2-flute	1.210	1.210	1.160	1.175	1.1888	0.02529	-1.503
74	2700	330	0.5	on	climb	1	2-flute	0.950	1.025	1.100	1.100	1.0438	0.07181	-0.387
75	3200	203	0.5	off	climb	1	2-flute	1.060	1.145	1.120	1.060	1.0963	0.04308	-0.803
76	3200	330	1	on	climb	1	2-flute	0.900	0.945	0.945	0.935	0.9313	0.02136	0.617
77	3200	330	0.5	on	climb	1	2-flute	0.920	0.995	1.050	1.050	1.0038	0.06156	-0.045
78	2700	203	0.5	on	conv	2	2-flute	1.025	1.100	1.100	1.310	1.1338	0.1227	-1.128
79	3200	330	1	off	conv	2	2-flute	1.370	1.395	1.310	1.525	1.4	0.09065	-2.936
80	2700	330	0.5	off	climb	2	2-flute	0.975	0.975	1.045	0.985	0.995	0.03367	0.0398
81	2700	203	1	on	climb	1	2-flute	1.060	1.100	1.070	1.025	1.0638	0.03092	-0.54
82	2700	203	1	off	conv	2	2-flute	2.050	2.050	2.750	2.150	2.25	0.33665	-7.116
83	3200	203	1	off	conv	1	2-flute	1.350	1.225	2.000	1.200	1.4438	0.37659	-3.406
84	2700	203	0.5	off	climb	1	2-flute	1.175	1.175	1.170	1.245	1.1913	0.03591	-1.523
85	3200	203	0.5	on	conv	1	2-flute	1.250	1.250	1.150	1.160	1.2025	0.055	-1.609
86	2700	330	1	on	conv	2	2-flute	1.150	1.210	1.220	1.250	1.2075	0.04193	-1.642
87	2700	330	1	on	conv	1	2-flute	1.135	1.160	1.110	1.160	1.1413	0.02394	-1.149
88	2700	330	0.5	on	climb	2	2-flute	0.995	1.085	1.185	1.135	1.1	0.08103	-0.845

Appendix B5. Full factorial data set for perpendicular measurement method (Full milling data set). ......continued

OBS	TS	WS	DC	C	DIC	CL	Tool	R1	R2	R3	R4	Mean	STD	STB
89	3200	203	0.5	on	climb	1	2-flute	1.035	1.110	1.085	1.070	1.075	0.03136	-0.631
90	2700	203	1	off	conv	1	2-flute	1.925	1.400	1.550	1.450	1.5813	0.2375	-4.053
91	2700	203	1	on	conv	2	2-flute	1.285	1.285	1.245	1.270	1.2713	0.01887	-2.085
92	3200	330	0.5	on	conv	1	2-flute	1.035	1.125	1.170	1.210	1.135	0.07517	-1.114
93	2700	330	1	on	climb	1	2-flute	1.245	1.350	1.320	1.260	1.2938	0.04956	-2.242
94	2700	203	1	on	climb	2	2-flute	1.045	0.995	1.020	1.010	1.0175	0.02102	-0.152
95	3200	203	1	on	climb	1	2-flute	0.820	0.945	0.935	0.945	0.9113	0.06102	0.7927
96	3200	330	0.5	on	climb	2	2-flute	1.085	1.150	1.185	1.420	1.21	0.146	-1.703
97	3200	330	0.5	off	climb	2	2-flute	1.460	1.260	1.175	1.150	1.2613	0.14062	-2.056
98	3200	330	0.5	off	climb	1	2-flute	1.410	1.485	1.545	1.275	1.4288	0.11643	-3.121
99	3200	203	1	off	conv	2	2-flute	2.135	1.570	1.460	2.300	1.8663	0.41359	-5.576
100	3200	203	0.5	on	conv	2	2-flute	1.120	1.135	1.260	1.285	1.2	0.08456	-1.6
101	3200	330	0.5	on	conv	2	2-flute	1.135	1.160	1.300	1.125	1.18	0.08134	-1.453
102	2700	203	1	off	climb	1	2-flute	1.125	1.120	1.135	1.185	1.1413	0.02983	-1.15
103	2700	203	0.5	off	conv	2	2-flute	1.235	1.085	1.170	1.150	1.16	0.06178	-1.298
104	2700	203	0.5	off	climb	2	2-flute	1.270	1.185	1.150	1.150	1.1888	0.05662	-1.509
105	3200	330	1	on	conv	2	2-flute	1.000	1.100	1.010	1.070	1.045	0.04796	-0.389
106	2700	330	0.5	off	conv	1	2-flute	1.300	1.195	1.170	1.110	1.1938	0.07931	-1.553
107	3200	203	1	on	climb	2	2-flute	1.010	1.160	1.075	1.125	1.0925	0.06513	-0.78
108	2700	330	1	off	climb	2	2-flute	0.960	1.060	1.085	1.000	1.0263	0.05677	-0.235
109	2700	330	1	off	conv	2	2-flute	2.400	1.850	2.050	2.750	2.2625	0.3966	-7.191
110	2700	203	0.5	on	climb	2	2-flute	1.210	1.210	1.260	1.220	1.225	0.0238	-1.764

Appendix B5. Full factorial data set for perpendicular measurement method (Full milling data set) ......continued

OBS	TS	WS	DC	C	DIC	CL	Tool	R1	R2	R3	R4	Mean	STD	STB
111	2700	203	1	on	conv	1	2-flute	1.195	1.225	1.225	1.225	1.2175	0.015	-1.71
112	2700	203	0.5	on	climb	1	2-flute	1.125	1.160	1.210	1.185	1.17	0.03629	-1.367
113	2700	330	0.5	off	conv	2	2-flute	1.375	1.360	1.235	1.225	1.2988	0.07973	-2.283
114	3200	330	0.5	off	conv	2	2-flute	1.310	1.325	1.175	1.245	1.2638	0.0686	-2.043
115	2700	330	1	off	conv	1	2-flute	1.300	1.650	1.500	2.100	1.6375	0.34004	-4.422
116	3200	330	1	off	climb	1	2-flute	1.160	1.235	1.235	1.235	1.2163	0.0375	-1.704
117	2700	330	0.5	on	conv	2	2-flute	1.235	1.185	1.200	1.185	1.2013	0.02358	-1.594
118	2700	330	1	on	climb	2	2-flute	0.935	1.060	1.120	1.120	1.0588	0.08721	-0.518
119	2700	203	0.5	off	conv	1	2-flute	1.620	1.235	1.010	1.085	1.2375	0.27162	-2.005
120	2700	203	1	off	climb	2	2-flute	0.985	0.985	0.970	0.985	0.9813	0.0075	0.1642
121	3200	203	0.5	off	conv	2	2-flute	3.325	2.350	2.300	2.200	2.5438	0.52455	-8.246
122	3200	203	0.5	off	conv	1	2-flute	1.685	1.285	1.295	1.385	1.4125	0.18715	-3.057
123	3200	203	1	off	climb	2	2-flute	1.010	1.020	1.035	1.110	1.0438	0.04535	-0.378
124	3200	330	1	off	climb	2	2-flute	1.070	0.985	0.960	0.960	0.9938	0.05218	0.0455
125	3200	203	0.5	off	climb	2	2-flute	1.060	1.050	1.070	1.085	1.0663	0.01493	-0.558
126	2700	330	0.5	off	climb	1	2-flute	1.135	1.045	1.000	0.985	1.0413	0.0675	-0.365
127	3200	330	1	on	conv	1	2-flute	1.120	1.120	1.145	1.200	1.1463	0.03772	-1.189
128	3200	203	1	on	conv	2	2-flute	1.110	1.200	1.210	1.120	1.16	0.05228	-1.296

Appendix B5. Continuation… full factorial data set for perpendicular measurement method (Full milling data set).

APPENDIX B6

TAGUCHI L_{16} DATA SETS FOR PERPENDICULAR MEASUREMENT METHOD FEATURING SURFACE ROUGHNESS RESPONSE (FULL MILLING DATA SET)

(N.B. Abbreviations as in Appendix B2)
(N.B.2. This data set was built based on data set in Appendix B5)

run	FF run equiv.	C	DIC	C*DIC	CL	C*CL	DIC*CL	WS*T	WS	C*WS	TS	C*TS	DC	C*DC	C*T	T	R1	R2	R3	R4	Mean	STD	STB
1	21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1.08	1.063	0.907	0.93	0.995	0.0891	0.017
2	126	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1.135	1.045	1.000	0.985	1.041	0.067	-0.365
3	125	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1.060	1.050	1.070	1.085	1.066	0.015	-0.558
4	27	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1.05	1.033	1.073	1.01	1.0415	0.02664	-0.355
5	90	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1.925	1.400	1.550	1.450	1.581	0.238	-4.053
6	36	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1.43	1.553	1.05	1.197	1.3075	0.22642	-2.425
7	30	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	7.53	6.4	7.9	5.3	6.78325	1.17703	-16.726
8	79	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1.370	1.395	1.310	1.525	1.400	0.091	-2.936
9	95	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	0.820	0.945	0.935	0.945	0.911	0.061	0.793
10	55	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	1.09	1	1.03	1.06	1.045	0.03873	-0.387
11	47	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	0.97	0.957	0.93	0.95	0.9525	0.01782	0.422
12	118	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	0.935	1.060	1.120	1.120	1.059	0.087	-0.518
13	63	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1.09	1.05	0.95	0.94	1.0075	0.07411	-0.082
14	92	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	1.035	1.125	1.170	1.210	1.135	0.075	-1.114
15	78	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1.025	1.100	1.100	1.310	1.134	0.123	-1.128
16	10	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	0.95	0.923	0.967	0.887	0.931	0.03441	0.617

Appendix B6. Taguchi data set for perpendicular measurement method (Full milling data set).), using Linear Graph II.

run	C	TS	C*TS	WS	C*WS	DC	C*DC	DIC	C*DIC	CL	C*CL	T	C*T	ERR	C*ERR	R1	R2	R3	R4	Mean	STD	STB
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1.08	1.063	0.907	0.93	0.995	0.089	0.017
2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2.135	1.570	1.460	2.300	1.866	0.414	-5.576
3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1.410	1.485	1.545	1.275	1.429	0.116	-3.121
4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	16.87	8.73	11.07	14.83	12.875	3.662	-22.451
5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1.073	1.003	1.073	1.087	1.059	0.038	-0.502
6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1.620	1.235	1.010	1.085	1.238	0.272	-2.005
7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	0.960	1.060	1.085	1.000	1.026	0.057	-0.235
8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	3.08	3.53	4.03	4.4	3.760	0.577	-11.580
9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	0.977	1.087	1.077	1.14	1.070	0.068	-0.603
10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	1.110	1.200	1.210	1.120	1.160	0.052	-1.296
11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	0.920	0.995	1.050	1.050	1.004	0.062	-0.045
12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	0.99	1.11	1.1	1.13	1.083	0.063	-0.700
13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1.24	1.14	1.09	1.15	1.155	0.062	-1.261
14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	1.210	1.210	1.160	1.175	1.189	0.025	-1.503
15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	0.935	1.060	1.120	1.120	1.059	0.087	-0.518
16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	0.933	0.907	0.913	0.913	0.917	0.011	0.757

Appendix B6. Taguchi data set for perpendicular measurement method (Full milling data set).), using Linear Graph IV

APPENDIX B7

VARIATION PERCENTAGE BETWEEN R_a VALUES FOR PERPENDICULAR AND PARALLEL DATA SETS

Abbreviations

Run – run number.

Repetitions:
R1 – Variation percentage repetition One.
R2 – Variation percentage repetition Two.
R3 – Variation percentage repetition Three.
R4 – Variation percentage repetition Four.
R5 – Variation percentage repetition Five.
R6 – Variation percentage repetition Six.
R7 – Variation percentage repetition Seven.
R8 – Variation percentage repetition Eight.

Each of these **R** represents the variation percentage of surface roughness between perpendicular and parallel values of the same run and repetition. For instance, the reported roughness value of the first run and the fifth repetition of the perpendicular data set is compared with the value of the first run and fifth repetition of the parallel data set. The variation percentage is given by:

$$R = \frac{100 \bullet (perpendicular - parallel)}{perpendicular}$$

Responses (Stats calculated for each run only):
Mean – Mean.

Notes:
N.A. – Data Not Available.
In all cases the non-availability of data was due to extreme values (high) of surface roughness, so the tester (Mitutoyo, 1989) was unable to report any measurement. N.A. measures were treated as missing values and therefore ignored for purposes of calculating statistics. This means that metrics (responses) were calculated considering only those repetitions with non-missing values.

Run	R1	R2	R3	R4	R5	R6	R7	R8	Mean
1	70.93	72.60	74.66	68.97	82.02	83.44	84.96	84.32	77.74
2	51.42	32.51	-24.10	37.56	67.82	47.46	20.62	38.61	33.99
3	85.34	79.69	79.75	81.08	78.35	84.51	82.03	74.28	80.63
4	58.50	63.12	65.66	61.71	85.73	89.68	88.15	82.57	74.39
5	60.66	53.36	60.90	66.81	64.77	71.83	69.66	70.68	64.84
6	89.13	88.49	84.49	83.60	59.04	66.50	64.41	61.09	74.59
7	87.60	85.74	85.37	85.28	84.40	82.57	84.16	82.81	84.74
8	88.11	83.90	85.97	87.03	81.84	82.81	79.20	82.46	83.91
9	56.87	55.33	57.91	62.24	77.56	75.87	70.43	76.70	66.61
10	65.89	71.51	67.94	69.22	71.61	75.41	60.54	72.91	69.38
11	72.10	75.58	70.68	67.74	74.36	75.20	72.31	73.91	72.74
12	64.72	62.84	67.50	59.05	66.91	72.51	74.49	71.51	67.44
13	46.99	50.86	53.61	63.09	78.57	75.91	69.40	68.91	63.42
14	6.13	53.01	50.35	58.12	31.34	55.81	4.39	37.26	37.05
15	52.10	58.54	59.51	60.44	40.08	51	48.67	53.86	53.03
16	76.03	70.90	82.27	71.01	73.27	71.17	81.08	77.70	75.43
17	84.28	84.11	86.74	84.14	87.85	86.33	87.46	85.11	85.75
18	10.68	-5.40	19.32	40.71	24.16	22.13	14.64	58.55	23.10
19	86.28	84.67	84.80	78.39	70.31	71.38	74.96	72.91	77.96
20	69.72	73.66	67.11	60.02	67.55	56.13	52.42	54	62.58
21	71.94	75.26	70.23	77.42	65.29	64.71	56.71	56.70	67.28
22	53.69	60.47	60.36	69.38	74.16	69.62	62.70	63.53	64.24
23	68.30	69.39	71.53	69.89	87.43	82.55	83.30	84.73	77.14

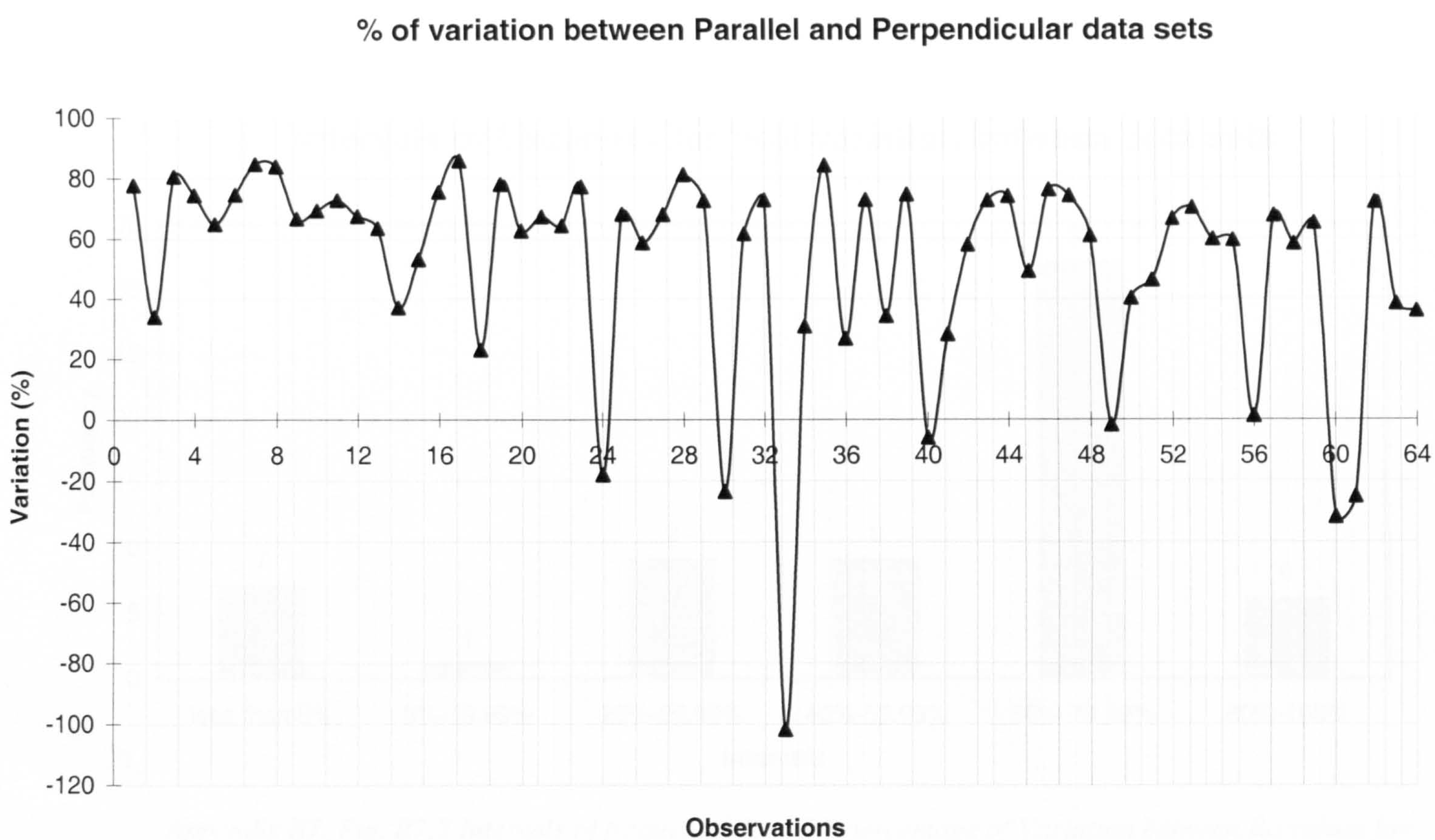
Appendix B7. Variation percentage between R_a values for perpendicular and parallel data sets…continued

Run	R1	R2	R3	R4	R5	R6	R7	R8	Mean
24	-20.75	-7.46	-10.00	-71.48	0.85	-66.75	-4.51	35.71	-18.05
25	73.45	70.43	77.96	73.53	62.96	61.25	67.75	57.13	68.06
26	60.52	57.69	53.76	57.73	68.32	40.38	66.27	63.89	58.57
27	71.71	79.67	79.78	72.97	53.06	63.65	58.93	63.49	67.91
28	82.37	82.56	84.38	78.31	77.52	79.28	83.05	81.16	81.08
29	82.91	85.19	85.24	83.25	56.51	64.91	57.96	64.30	72.53
30	-4.87	29.22	14.34	23.91	N.A.	9.08	14.76	10.15	13.80
31	68.18	71.80	68.54	70.19	50.83	50.15	54.22	58.13	61.50
32	69.84	66.64	61.03	59.05	79.23	80.56	83.16	82.04	72.69
33	N.A.	N.A.	N.A.	N.A.	N.A.	-101.85	N.A.	N.A.	-101.85
34	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	30.92	N.A.	30.92
35	83.33	82.09	84.13	84.44	85.41	84.50	85.57	83.92	84.17
36	-0.70	28.72	10.48	17.29	43.93	24.25	34.10	56.65	26.84
37	80.64	76.77	74.73	74.88	68.53	67.71	69.70	69.72	72.83
38	57.84	52.02	33.65	54.67	17.93	22.34	29.41	6.53	34.30
39	75.63	75.59	76.78	75.69	74.20	73.08	80.00	66.04	74.63
40	20.91	N.A.	-5.72	-26.50	16.20	4.24	8.30	-58.54	-5.87
41	10.25	24.05	24.82	41.84	37.21	18.82	17.58	50.86	28.18
42	43.60	55.14	61.32	67.00	54.37	60.28	60.03	62.26	58.00
43	67.65	67.23	65.54	69.57	76.23	78.48	77.30	78.76	72.59
44	61.90	67.71	66.11	67.93	82.99	81.98	81.11	82.75	74.06
45	34.62	37.51	49.23	49.22	10.19	72.66	74.47	65.55	49.18
46	76.91	81.73	80.16	78.64	76.25	60.25	79.19	76.53	76.21

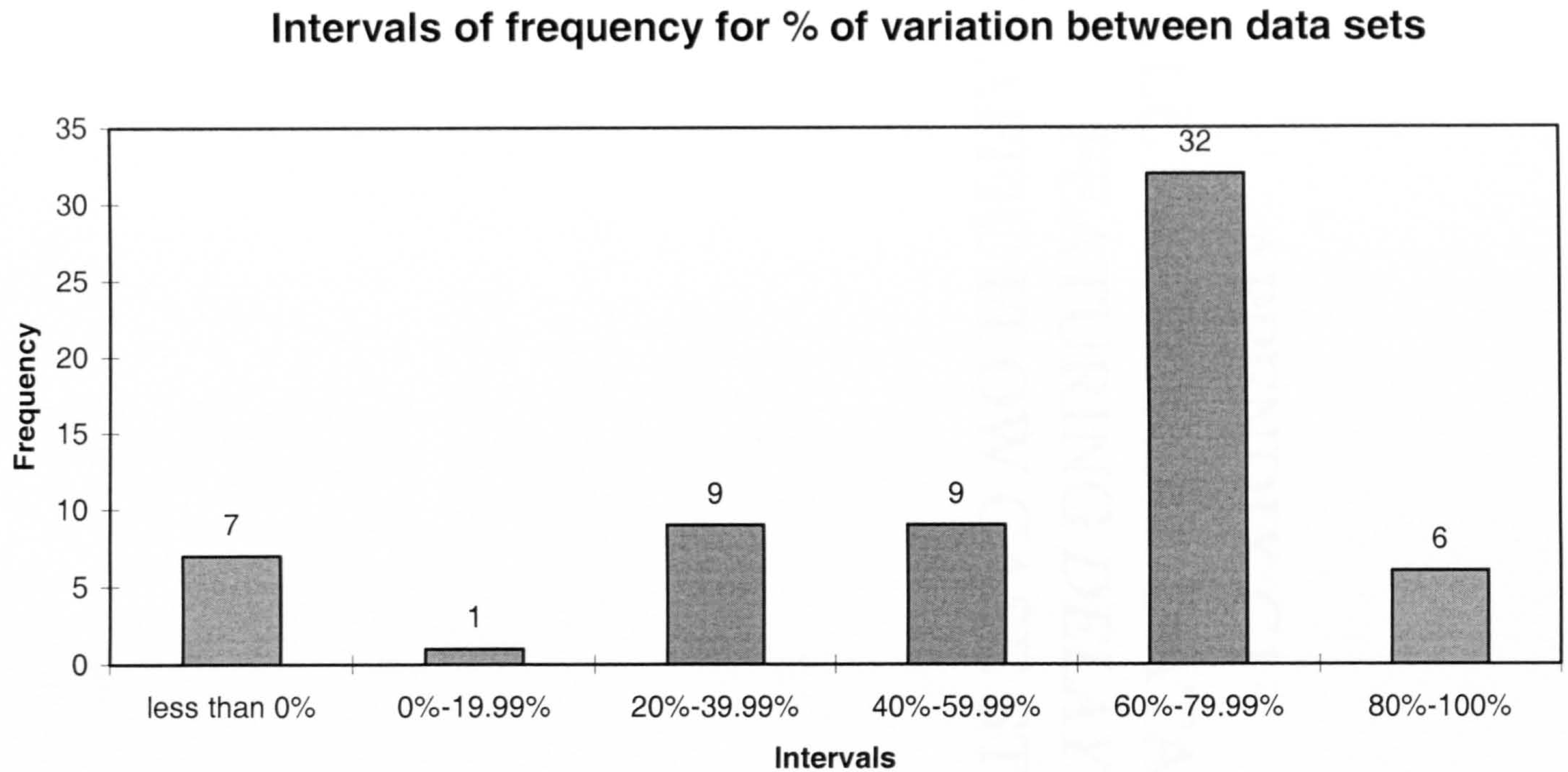
Appendix B7. Variation percentage between Ra values for perpendicular and parallel data sets…continued

Run	R1	R2	R3	R4	R5	R6	R7	R8	Mean
47	72.97	72.52	73.12	70.53	75.97	77.57	75.86	75.34	74.23
48	62.19	61.19	71.08	62.28	59.03	73.46	49.29	48.97	60.94
49	23.08	-5.75	-52.53	3.88	13.89	-6.25	15.67	-5.42	-1.68
50	32.14	25.32	37.43	1.85	62.70	53.64	60.38	48.23	40.21
51	33.15	33.54	45.05	47.42	44.24	13.95	75.00	77.14	46.19
52	57.58	60.36	63.00	71.42	74.74	73.40	64.06	68.02	66.57
53	59.63	60.78	61.55	64.76	79.33	82.90	75.78	77.43	70.27
54	67.42	58.47	69.76	69.76	51.98	56.24	50.57	53.95	59.77
55	51.38	57.00	51.46	54.43	59.05	69.22	70.48	62.86	59.48
56	-6.25	-14.39	50.51	-29.41	32.02	N.A.	-24.53	N.A.	1.32
57	51.77	68.70	67.03	69.70	78.51	66.28	68.13	71.26	67.67
58	51.69	52.12	45.00	48.52	61.44	62.92	70.12	73.86	58.21
59	81.51	79.81	79.81	55.63	42.04	60.48	66.26	55.65	65.15
60	-57.72	-65.34	-29.81	-25.93	-6.55	N.A.	-5.07	N.A.	-31.74
61	N.A.	-45.48	-21.95	-31.49	1.22	19.94	-57.39	-40.28	-25.06
62	77.18	72.54	72.75	74.78	73.48	69.64	64.15	71.44	72.00
63	39.72	36.86	34.42	25.85	29.09	35.98	56.89	47.59	38.30
64	-29.87	48.16	51.12	52.27	63.05	-10.00	44.69	67.41	35.85
OA	53.13	54.77	54.64	54.05	58.73	54.81	55.81	59.93	52.31

Appendix B7. Continuation.... variation percentage between Ra values for perpendicular and parallel data sets



Appendix B7. Fig. B7.1 Plot for Percentage of Variation between Ra values for perpendicular and parallel data sets



Appendix B7. Fig. B7.2 Intervals of frequency chart for percentage of Variation between Ra values for perpendicular and parallel data sets

APPENDIX C1
FULL FACTORIAL DATA SET
FEATURING *DELAY*
(TRAFFIC FLOW CASE STUDY)

Abbreviations

Run – run number.

Factors:
VM - Vehicle Mix (%HGV).
SD – Speed Distribution (km/hr).
PS1 – Profile 1 Slope.
PS2 – Profile 2 Slope.
PS3 – Profile 3 Slope.
PM1 - Profile 1 Magnitude.
PM2 - Profile 2 Magnitude.
PM3 - Profile 3 Magnitude.
CP – Controller Type.

Repetitions:
R1 – Repetition One.
R2 – Repetition Two.
R3 – Repetition Three.
R4 – Repetition Four.
R5 – Repetition Five.
R6 – Repetition Six.
R7 – Repetition Seven.
R8 – Repetition Eight.
Delay – Delay
Vehs – Number of vehicles corresponding to Delay

Responses (Stats calculated for each run only):
Mean – Mean.
Median - Median
STD – Standard Deviation.
SNR – Signal-to-Noise Ratio.

												R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
1	1	1	1	1	1	1	1	1	1	13	1,292	13	1,370	13	1,270	13	1,435	13	1,187	14	1,268	13	1,279	13	1,320	1.239	13.00	0.03431	-1.863
2	1	1	1	1	1	1	1	2	1	14	1,471	14	1,583	14	1,504	15	1,540	14	1,478	15	1,511	13	1,451	14	1,557	3.052	14.00	1.00490	-10.086
3	1	1	1	1	1	1	2	1	1	12	1,908	12	1,911	12	1,833	12	2,022	12	1,794	11	1,891	12	1,925	12	1,979	0.948	12.00	0.04447	0.460
4	1	1	1	1	1	1	2	2	1	12	2,020	12	1,973	12	2,055	12	2,068	12	2,156	12	2,048	13	2,112	13	2,078	1.042	12.00	0.01692	-0.355
5	1	1	1	1	1	2	1	1	1	14	1,845	14	1,858	13	1,912	14	1,811	14	1,936	14	1,926	14	1,830	14	1,800	0.907	14.00	0.01741	0.846
6	1	1	1	1	1	2	1	2	1	15	2,069	15	1,927	15	2,142	15	1,937	16	2,005	15	1,766	15	2,015	15	1,865	1.173	15.00	0.03045	-1.390
7	1	1	1	1	1	2	2	1	1	12	2,392	13	2,334	13	2,398	13	2,286	13	2,325	13	2,327	14	2,372	13	2,355	1.067	13.00	0.02943	-0.566
8	1	1	1	1	1	2	2	2	1	14	2,579	14	2,453	14	2,554	15	2,606	14	2,499	13	2,447	14	2,352	13	2,442	1.166	14.00	0.04960	-1.337
9	1	1	1	1	2	1	1	1	1	13	1,440	13	1,291	14	1,171	13	1,377	13	1,321	13	1,367	13	1,350	13	1,306	0.971	13.00	0.02410	0.253
10	1	1	1	1	2	1	1	2	1	14	1,405	14	1,446	14	1,481	14	1,610	14	1,463	14	1,383	13	1,369	15	1,307	0.916	14.00	0.03209	0.757
11	1	1	1	1	2	1	2	1	1	12	1,815	13	1,898	12	1,793	13	2,043	12	1,961	12	1,930	12	1,988	12	1,953	0.913	12.00	0.02256	0.788
12	1	1	1	1	2	1	2	2	1	12	1,938	12	2,092	13	2,084	13	2,091	13	1,975	13	2,043	13	2,167	13	2,079	0.873	13.00	0.03055	1.171
13	1	1	1	1	2	2	1	1	1	14	1,833	14	1,867	14	1,725	14	1,779	14	1,895	14	1,813	14	1,807	14	1,806	0.957	14.00	0.03125	0.381
14	1	1	1	1	2	2	1	2	1	15	2,005	16	1,970	15	1,950	15	1,924	16	2,218	16	2,067	16	1,985	16	2,059	1.603	16.00	0.32385	-4.249
15	1	1	1	1	2	2	2	1	1	13	2,375	13	2,269	12	2,293	14	2,525	0	0	14	2,336	13	2,353	13	2,289	1.025	13.00	0.04680	-0.218
16	1	1	1	1	2	2	2	2	1	14	2,535	14	2,619	15	2,589	14	2,430	15	2,590	14	2,553	14	2,524	14	2,550	0.818	14.00	0.04546	1.735
17	1	1	1	2	1	1	1	1	1	14	1,307	14	1,177	13	1,398	13	1,291	13	1,357	14	1,353	13	1,402	13	1,302	0.981	13.00	0.03664	0.160
18	1	1	1	2	1	1	1	2	1	14	1,628	15	1,443	14	1,595	14	1,487	14	1,425	13	1,411	14	1,618	15	1,484	1.86	14.00	0.58373	-5.748
19	1	1	1	2	1	1	2	1	1	12	2,024	12	1,957	12	1,846	13	1,950	12	1,905	12	1,790	12	1,835	12	1,756	1.227	12.00	0.04963	-1.784
20	1	1	1	2	1	1	2	2	1	12	1,961	13	1,803	13	2,066	12	1,993	13	2,076	13	2,132	13	2,077	13	2,113	1.014	13.00	0.05568	-0.132
21	1	1	1	2	1	2	1	1	1	15	1,912	14	1,892	15	1,862	14	1,889	14	1,844	14	1,713	15	1,888	14	1,784	0.988	14.00	0.06532	0.088
22	1	1	1	2	1	2	1	2	1	14	1,848	15	2,151	14	1,843	16	2,015	15	1,878	15	1,768	14	1,950	15	1,957	0.871	15.00	0.05022	1.186

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)…(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
23	1	1	1	2	1	2	2	1	1	14	2,224	14	2,409	13	2,297	13	2,283	14	2,412	14	2,457	14	2,322	14	2,361	13.75	14.00	1077.628	-22.77
24	1	1	1	2	1	2	2	2	1	15	2,628	14	2,528	14	2,555	15	2,598	14	2,526	15	2,497	15	2,649	14	2,511	14.5	14.50	1188.168	-23.23
25	1	1	1	2	2	1	1	1	1	13	1,248	12	1,232	13	1,232	13	1,282	13	1,337	12	1,295	13	1,391	13	1,260	12.75	13.00	608.7316	-22.12
26	1	1	1	2	2	1	1	2	1	14	1,466	14	1,538	13	1,464	13	1,491	14	1,601	13	1,523	13	1,491	14	1,508	13.5	13.50	687.8995	-22.61
27	1	1	1	2	2	1	2	1	1	11	1,871	11	1,876	12	2,001	12	1,809	11	2,007	11	1,862	12	1,872	12	1,940	11.5	11.50	877.2486	-21.22
28	1	1	1	2	2	1	2	2	1	12	2,069	12	1,880	12	2,079	12	1,942	13	1,992	12	1,994	12	2,270	12	2,077	12.125	12.00	1001.832	-21.68
29	1	1	1	2	2	2	1	1	1	13	1,920	14	1,769	14	1,872	14	1,927	14	1,917	14	1,775	14	1,856	14	1,754	13.875	14.00	829.5971	-22.85
30	1	1	1	2	2	2	1	2	1	15	2,103	15	1,964	15	1,891	15	1,943	15	1,884	15	2,135	15	2,114	14	1,936	14.875	15.00	931.6646	-23.45
31	1	1	1	2	2	2	2	1	1	13	2,247	13	2,306	13	2,467	13	2,503	13	2,295	13	2,324	13	2,312	13	2,270	13	13.00	1054.569	-22.28
32	1	1	1	2	2	2	2	2	1	14	2,711	14	2,561	14	2,476	14	2,621	15	2,731	14	2,644	14	2,698	13	2,466	14	14.00	1190.292	-22.93
33	1	1	2	1	1	1	1	1	1	13	1,373	13	1,431	13	1,460	14	1,412	12	1,335	13	1,276	12	1,417	13	1,378	12.875	13.00	640.9839	-22.20
34	1	1	2	1	1	1	1	2	1	13	1,596	14	1,366	14	1,418	13	1,427	13	1,602	14	1,506	14	1,372	14	1,553	13.625	14.00	672.4989	-22.69
35	1	1	2	1	1	1	2	1	1	12	1,817	12	1,893	12	1,894	12	1,985	12	1,802	11	1,908	12	1,891	12	1,877	11.875	12.00	866.6529	-21.50
36	1	1	2	1	1	1	2	2	1	12	1,974	13	2,023	12	2,163	12	1,901	12	2,001	12	1,950	12	2,167	12	1,975	12.125	12.00	954.4351	-21.68
37	1	1	2	1	1	2	1	1	1	14	1,870	14	1,776	14	1,830	15	1,841	15	1,754	13	1,895	14	1,735	14	1,852	14.125	14.00	824.2649	-23.01
38	1	1	2	1	1	2	1	2	1	15	2,076	15	1,811	15	2,056	15	1,881	14	1,970	15	1,864	16	2,099	15	1,980	15	15.00	937.7781	-23.53
39	1	1	2	1	1	2	2	1	1	13	2,428	13	2,332	13	2,465	13	2,428	13	2,355	13	2,407	13	2,498	13	2,364	13	13.00	1119.889	-22.28
40	1	1	2	1	1	2	2	2	1	13	2,479	14	2,598	13	2,591	14	2,625	14	2,549	14	2,528	14	2,592	13	2,464	13.625	14.00	1164.413	-22.69
41	1	1	2	1	2	1	1	1	1	13	1,213	13	1,381	13	1,324	13	1,327	13	1,260	13	1,378	13	1,267	13	1,360	13	13.00	602.5274	-22.28
42	1	1	2	1	2	1	1	2	1	14	1,572	14	1,411	14	1,615	14	1,551	14	1,617	14	1,393	15	1,522	15	1,619	14.25	14.00	720.9857	-23.08
43	1	1	2	1	2	1	2	1	1	13	1,789	13	1,934	12	1,884	13	1,771	13	1,768	13	1,946	13	1,818	13	2,067	12.875	13.00	895.7376	-22.20
44	1	1	2	1	2	1	2	2	1	12	2,124	13	1,978	13	2,161	13	2,016	13	2,082	13	2,136	13	2,113	13	2,110	12.875	13.00	971.4943	-22.20

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
45	1	1	2	1	2	2	1	1	1	14	1,825	14	1,792	15	1,801	15	1,981	14	1,865	14	1,879	14	1,806	15	1,892	14.375	14.00	849.597	-23.157
46	1	1	2	1	2	2	1	2	1	16	2,028	15	2,038	16	2,077	15	1,921	16	2,025	16	2,063	16	2,072	15	1,998	15.625	16.00	934.979	-23.881
47	1	1	2	1	2	2	2	1	1	13	2,412	14	2,477	13	2,436	13	2,292	14	2,202	14	2,266	14	2,335	14	2,406	13.625	14.00	1091.244	-22.692
48	1	1	2	1	2	2	2	2	1	15	2,665	15	2,696	14	2,486	14	2,476	15	2,575	15	2,481	14	2,507	14	2,497	14.5	14.50	1151.415	-23.233
49	1	1	2	2	1	1	1	1	1	12	1,315	13	1,376	12	1,253	12	1,384	13	1,320	14	1,366	13	1,386	12	1,270	12.625	12.50	609.670	-22.038
50	1	1	2	2	1	1	1	2	1	15	1,529	14	1,556	15	1,537	14	1,611	14	1,517	14	1,420	14	1,423	14	1,567	14.25	14.00	686.495	-23.080
51	1	1	2	2	1	1	2	1	1	12	1,833	12	1,686	12	1,965	12	2,000	12	1,954	12	2,068	12	1,819	12	1,794	12	12.00	830.719	-21.584
52	1	1	2	2	1	1	2	2	1	13	2,004	13	2,172	13	1,954	13	1,815	12	1,970	12	2,122	12	2,119	13	2,165	12.625	13.00	985.767	-22.031
53	1	1	2	2	1	2	1	1	1	14	1,802	14	1,790	14	1,879	15	1,764	14	1,948	14	1,870	14	1,840	14	1,741	14.125	14.00	822.708	-23.002
54	1	1	2	2	1	2	1	2	1	16	1,835	15	2,004	16	2,075	15	2,032	16	2,078	16	2,105	15	1,818	15	1,895	15.5	15.50	852.389	-23.811
55	1	1	2	2	1	2	2	1	1	13	2,478	14	2,378	13	2,483	13	2,432	14	2,158	13	2,379	13	2,394	13	2,277	13.25	13.00	1075.409	-22.449
56	1	1	2	2	1	2	2	2	1	14	2,554	14	2,463	14	2,417	15	2,593	14	2,522	14	2,529	15	2,542	14	2,615	14.25	14.00	1187.216	-23.080
57	1	1	2	2	2	1	1	1	1	13	1,565	14	1,357	14	1,308	13	1,331	14	1,305	13	1,304	14	1,285	13	1,420	13.5	13.50	620.886	-22.613
58	1	1	2	2	2	1	1	2	1	14	1,469	15	1,612	15	1,384	14	1,476	14	1,495	14	1,301	15	1,468	14	1,506	14.375	14.00	681.788	-23.157
59	1	1	2	2	2	1	2	1	1	12	2,052	11	1,883	12	2,001	12	1,879	12	1,823	12	1,922	12	1,843	12	1,852	11.875	12.00	849.752	-21.496
60	1	1	2	2	2	1	2	2	1	12	2,022	13	2,070	13	2,071	12	1,944	13	2,118	12	2,233	12	2,037	13	2,112	12.5	12.50	954.731	-21.945
61	1	1	2	2	2	2	1	1	1	14	1,782	14	1,835	14	1,713	14	1,753	15	1,731	14	1,828	14	1,871	14	1,734	14.125	14.00	828.647	-23.002
62	1	1	2	2	2	2	1	2	1	16	2,087	15	2,020	15	1,975	15	1,926	16	1,979	16	2,030	15	2,097	17	2,114	15.625	15.50	967.493	-23.885
63	1	1	2	2	2	2	2	1	1	13	2,413	13	2,448	14	2,394	13	2,360	14	2,599	13	2,238	13	2,522	13	2,523	13.25	13.00	1161.519	-22.449
64	1	1	2	2	2	2	2	2	1	15	2,608	14	2,465	15	2,571	15	2,483	15	2,587	15	2,698	14	2,482	14	2,518	14.625	15.00	1150.449	-23.307
65	1	2	1	1	1	1	1	1	1	13	1,396	13	1,307	13	1,363	14	1,357	12	1,339	15	1,212	13	1,447	13	1,267	13.25	13.00	623.855	-22.461
66	1	2	1	1	1	1	1	2	1	15	1,591	14	1,545	14	1,527	14	1,382	13	1,463	15	1,487	14	1,411	13	1,546	14	14.00	678.814	-22.934

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
67	1	2	1	1	1	1	2	1	1	12	1,809	12	1,916	12	1,719	13	1,822	11	1,738	12	2,070	12	1,918	13	1,870	12.125	12.00	871.2913	- 21.68
68	1	2	1	1	1	1	2	2	1	12	2,042	12	2,050	12	2,015	13	2,032	12	2,002	13	2,096	13	1,940	13	2,081	12.5	12.50	925.7388	- 21.95
69	1	2	1	1	1	2	1	1	1	14	1,992	15	1,778	14	1,898	14	1,792	14	1,855	14	1,848	14	1,859	14	1,845	14.125	14.00	850.7598	- 23.00
70	1	2	1	1	1	2	1	2	1	16	1,952	15	2,000	16	1,912	16	2,219	15	1,947	15	2,054	15	1,980	15	1,947	15.375	15.00	901.792	- 23.74
71	1	2	1	1	1	2	2	1	1	13	2,434	14	2,533	14	2,450	13	2,284	14	2,385	14	2,316	13	2,382	13	2,468	13.5	13.50	1116.467	- 22.61
72	1	2	1	1	1	2	2	2	1	14	2,599	14	2,569	15	2,472	14	2,603	14	2,586	14	2,528	14	2,473	14	2,544	14.125	14.00	1154.808	- 23.00
73	1	2	1	1	2	1	1	1	1	13	1,263	13	1,347	13	1,338	13	1,372	13	1,444	13	1,341	13	1,318	13	1,395	13	13.00	622.26	- 22.28
74	1	2	1	1	2	1	1	2	1	14	1,567	14	1,424	14	1,413	14	1,555	14	1,431	14	1,543	14	1,596	15	1,410	14.125	14.00	691.0633	- 23.00
75	1	2	1	1	2	1	2	1	1	12	1,920	13	1,937	12	1,857	12	1,835	13	2,019	12	1,856	12	1,805	13	1,956	12.375	12.00	865.7344	- 21.86
76	1	2	1	1	2	1	2	2	1	13	2,052	13	2,095	13	1,907	13	2,046	13	1,980	12	1,958	12	1,980	13	2,068	12.75	13.00	931.2864	- 22.12
77	1	2	1	1	2	2	1	1	1	14	1,987	15	1,930	14	1,667	14	1,821	14	1,777	14	1,883	15	1,942	15	1,725	14.375	14.00	844.1823	- 23.16
78	1	2	1	1	2	2	1	2	1	15	2,208	16	2,021	16	2,038	15	1,865	16	1,957	16	2,067	15	1,939	16	2,107	15.625	16.00	930.299	- 23.88
79	1	2	1	1	2	2	2	1	1	13	2,403	13	2,431	13	2,389	14	2,268	14	2,408	13	2,402	13	2,368	13	2,433	13.25	13.00	1105.18	- 22.45
80	1	2	1	1	2	2	2	2	1	14	2,509	14	2,672	14	2,465	15	2,646	15	2,644	14	2,582	14	2,386	13	2,529	14.125	14.00	1131.612	- 23.01
81	1	2	1	2	1	1	1	1	1	14	1,375	13	1,250	13	1,294	13	1,275	13	1,331	14	1,346	14	1,484	12	1,307	13.25	13.00	641.5654	- 22.46
82	1	2	1	2	1	1	1	2	1	15	1,564	15	1,503	14	1,488	14	1,668	14	1,358	15	1,633	14	1,705	15	1,587	14.5	14.50	755.8961	- 23.23
83	1	2	1	2	1	1	2	1	1	12	1,731	13	1,860	13	1,959	12	1,851	12	1,723	13	1,879	12	1,922	13	1,757	12.5	12.50	846.8857	- 21.95
84	1	2	1	2	1	1	2	2	1	13	2,104	13	1,962	13	2,092	13	1,984	13	2,036	13	1,939	13	2,009	13	2,068	13	13.00	937.7569	- 22.28
85	1	2	1	2	1	2	1	1	1	14	1,845	14	1,908	14	1,811	14	1,761	15	1,941	15	1,931	15	1,841	15	1,750	14.5	14.50	824.8787	- 23.23
86	1	2	1	2	1	2	1	2	1	16	1,937	16	2,078	15	2,080	15	2,048	17	2,195	16	1,974	16	1,990	16	1,957	15.875	16.00	906.2667	- 24.02
87	1	2	1	2	1	2	2	1	1	14	2,359	14	2,326	14	2,320	14	2,278	14	2,384	14	2,354	14	2,529	14	2,308	14	14.00	1114.633	- 22.92
88	1	2	1	2	1	2	2	2	1	14	2,606	15	2,640	15	2,579	15	2,569	14	2,448	15	2,577	15	2,619	15	2,752	14.75	15.00	1236.867	- 23.38

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)…(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
89	1	2	1	2	2	1	1	1	1	12	1,265	13	1,338	13	1,302	12	1,190	12	1,225	12	1,220	12	1,435	12	1,306	12.25	12.00	629.654	-21.768
90	1	2	1	2	2	1	1	2	1	14	1,574	14	1,602	14	1,436	14	1,460	15	1,640	13	1,522	15	1,554	14	1,361	14.125	14.00	670.199	-23.008
91	1	2	1	2	2	1	2	1	1	12	1,834	11	1,800	11	1,664	12	1,879	13	1,943	12	1,915	11	1,876	12	1,905	11.75	12.00	869.688	-21.414
92	1	2	1	2	2	1	2	2	1	12	1,792	12	1,926	12	2,063	12	1,923	12	1,888	13	1,971	12	2,049	12	1,989	12.125	12.00	929.122	-21.677
93	1	2	1	2	2	2	1	1	1	14	1,740	15	1,943	14	1,693	14	1,677	14	1,919	15	1,960	14	1,743	14	1,850	14.25	14.00	825.478	-23.080
94	1	2	1	2	2	2	1	2	1	15	1,995	16	2,124	15	2,003	16	1,944	14	1,928	14	1,955	15	1,894	16	1,941	15.125	15.00	880.776	-23.605
95	1	2	1	2	2	2	2	1	1	14	2,298	14	2,381	13	2,124	13	2,353	13	2,489	13	2,460	13	2,389	13	2,308	13.25	13.00	1081.189	-22.449
96	1	2	1	2	2	2	2	2	1	14	2,580	14	2,534	14	2,636	14	2,304	14	2,557	14	2,537	14	2,527	14	2,552	14	14.00	1169.098	-22.923
97	1	2	2	1	1	1	1	1	1	13	1,434	14	1,312	13	1,265	13	1,319	13	1,269	13	1,347	12	1,350	12	1,265	12.875	13.00	599.591	-22.204
98	1	2	2	1	1	1	1	2	1	13	1,444	14	1,408	14	1,516	13	1,528	14	1,565	13	1,486	14	1,472	14	1,459	13.625	14.00	672.155	-22.692
99	1	2	2	1	1	1	2	1	1	12	2,003	12	1,862	12	1,883	12	2,060	12	1,941	12	1,862	12	1,950	12	1,866	12	12.00	877.965	-21.584
100	1	2	2	1	1	1	2	2	1	12	1,972	12	2,051	12	2,025	13	2,246	12	2,075	12	2,095	12	2,023	12	2,006	12.125	12.00	926.911	-21.677
101	1	2	2	1	1	2	1	1	1	14	1,899	13	1,773	14	1,773	14	1,858	15	1,878	14	1,915	13	1,797	14	1,904	13.875	14.00	850.615	-22.853
102	1	2	2	1	1	2	1	2	1	15	1,964	15	2,044	15	2,028	15	2,080	15	2,036	15	1,928	15	2,093	15	1,989	15	15.00	938.268	-23.522
103	1	2	2	1	1	2	2	1	1	13	2,357	14	2,399	13	2,384	13	2,379	13	2,374	13	2,329	12	2,327	13	2,404	13	13.00	1089.113	-22.285
104	1	2	2	1	1	2	2	2	1	14	2,602	14	2,695	14	2,596	14	2,364	14	2,493	14	2,358	14	2,564	13	2,484	13.875	14.00	1162.101	-22.847
105	1	2	2	1	2	1	1	1	1	13	1,294	14	1,264	13	1,350	13	1,334	13	1,277	14	1,370	14	1,302	13	1,416	13.375	13.00	623.667	-22.532
106	1	2	2	1	2	1	1	2	1	14	1,438	15	1,343	15	1,387	14	1,454	14	1,568	14	1,356	14	1,575	14	1,437	14.25	14.00	691.492	-23.080
107	1	2	2	1	2	1	2	1	1	13	1,944	13	1,850	13	1,839	12	1,960	12	1,672	13	1,892	12	1,895	13	1,787	12.625	13.00	846.846	-22.031
108	1	2	2	1	2	1	2	2	1	13	2,035	13	2,117	13	2,011	13	2,076	13	2,140	13	2,044	13	2,164	13	1,994	13	13.00	957.451	-22.279
109	1	2	2	1	2	2	1	1	1	14	1,767	15	1,881	14	1,889	15	1,763	14	1,769	15	1,786	15	1,975	14	1,859	14.5	14.50	881.232	-23.233
110	1	2	2	1	2	2	1	2	1	16	1,995	15	1,849	15	1,932	15	1,937	16	2,061	15	2,029	16	2,062	16	2,039	15.5	15.50	942.119	-23.811

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
111	1	2	2	1	2	2	2	1	1	14	2,464	14	2,397	14	2,579	15	2,455	14	2,340	14	2,336	14	2,353	14	2,438	14.125	14.00	1102.577	-23.002
112	1	2	2	1	2	2	2	2	1	15	2,483	14	2,429	14	2,454	14	2,550	14	2,491	14	2,529	14	2,515	14	2,464	14.125	14.00	1145.938	-23.002
113	1	2	2	2	1	1	1	1	1	13	1,377	14	1,296	13	1,174	14	1,260	14	1,412	14	1,273	13	1,299	13	1,285	13.5	13.50	591.765	-22.613
114	1	2	2	2	1	1	1	2	1	14	1,470	15	1,501	14	1,348	15	1,664	14	1,476	14	1,414	15	1,564	14	1,417	14.375	14.00	684.461	-23.157
115	1	2	2	2	1	1	2	1	1	13	2,015	12	1,950	13	1,954	13	2,111	12	1,830	13	1,925	12	1,842	12	1,821	12.5	12.50	841.975	-21.945
116	1	2	2	2	1	1	2	2	1	13	2,108	12	2,135	13	2,120	14	2,105	13	2,122	13	2,004	13	2,061	13	2,129	13	13.00	963.950	-22.285
117	1	2	2	2	1	2	1	1	1	15	1,901	15	1,723	14	1,845	15	1,949	14	1,824	15	1,787	14	1,873	14	1,792	14.5	14.50	841.772	-23.233
118	1	2	2	2	1	2	1	2	1	16	2,063	15	1,982	15	1,843	16	2,108	16	2,040	15	1,941	15	1,859	16	1,864	15.5	15.50	854.533	-23.811
119	1	2	2	2	1	2	2	1	1	13	2,537	13	2,367	14	2,316	13	2,344	13	2,510	13	2,272	14	2,319	13	2,323	13.25	13.00	1068.320	-22.449
120	1	2	2	2	1	2	2	2	1	14	2,639	15	2,512	15	2,730	14	2,470	14	2,551	14	2,438	15	2,596	14	2,666	14.375	14.00	1211.426	-23.157
121	1	2	2	2	2	1	1	1	1	14	1,418	14	1,344	13	1,245	13	1,491	14	1,265	13	1,415	13	1,348	13	1,345	13.375	13.00	617.060	-22.532
122	1	2	2	2	2	1	1	2	1	15	1,444	14	1,495	15	1,438	14	1,593	15	1,576	14	1,408	14	1,621	15	1,485	14.5	14.50	713.114	-23.233
123	1	2	2	2	2	1	2	1	1	13	1,947	12	1,772	12	1,792	12	1,824	12	1,918	13	1,920	12	1,926	12	2,016	12.25	12.00	907.006	-21.768
124	1	2	2	2	2	1	2	2	1	12	2,018	13	2,043	13	1,924	13	2,054	12	2,106	13	2,082	13	2,009	13	2,098	12.75	13.00	945.022	-22.115
125	1	2	2	2	2	2	1	1	1	14	1,901	14	1,885	14	1,821	14	1,748	14	1,914	14	1,760	13	1,703	14	1,904	13.875	14.00	830.118	-22.847
126	1	2	2	2	2	2	1	2	1	15	1,977	15	2,010	16	2,013	17	2,050	15	1,950	15	1,912	16	2,103	15	2,020	15.5	15.00	947.374	-23.816
127	1	2	2	2	2	2	2	1	1	14	2,422	13	2,312	13	2,377	13	2,401	13	2,391	14	2,572	14	2,462	13	2,380	13.375	13.00	1114.749	-22.532
128	1	2	2	2	2	2	2	2	1	15	2,384	15	2,777	15	2,654	14	2,668	15	2,702	14	2,572	14	2,306	14	2,408	14.5	14.50	1084.632	-23.233
129	2	1	1	1	1	1	1	1	1	14	1,330	14	1,243	13	1,447	14	1,272	13	1,325	14	1,363	13	1,220	14	1,235	13.625	14.00	561.910	-22.692
130	2	1	1	1	1	1	1	2	1	16	1,507	14	1,391	16	1,510	15	1,468	14	1,507	16	1,510	14	1,410	14	1,367	14.875	14.50	635.834	-23.466
131	2	1	1	1	1	1	2	1	1	12	1,937	12	1,799	12	2,024	13	1,944	13	2,153	13	1,890	12	1,861	12	1,838	12.375	12.00	850.388	-21.858
132	2	1	1	1	1	1	2	2	1	14	2,064	13	1,873	15	2,148	15	1,980	15	2,078	15	1,883	13	1,921	14	2,128	14.25	14.50	932.093	-23.091

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
133	2	1	1	1	1	2	1	1	1	18	1,931	16	1,729	16	1,748	14	1,739	17	1,863	17	1,783	16	1,905	16	1,731	16.25	16.00	835.306	-24.237
134	2	1	1	1	1	2	1	2	1	19	1,806	18	1,884	20	1,836	19	1,962	19	1,981	20	1,751	20	2,042	19	1,970	19.25	19.00	919.927	-25.694
135	2	1	1	1	1	2	2	1	1	17	2,176	14	2,143	14	2,411	14	2,188	15	2,375	15	2,246	14	2,369	15	2,313	14.75	14.50	1076.910	-23.395
136	2	1	1	1	1	2	2	2	1	17	2,649	17	2,632	16	2,401	18	2,595	19	2,389	20	2,710	22	2,564	18	2,603	18.375	18.00	1187.719	-25.326
137	2	1	1	1	2	1	1	1	1	13	1,377	13	1,341	14	1,352	13	1,343	13	1,481	13	1,233	14	1,344	13	1,242	13.25	13.00	593.075	-22.449
138	2	1	1	1	2	1	1	2	1	16	1,417	16	1,543	17	1,588	15	1,575	15	1,429	16	1,497	16	1,479	16	1,498	15.875	16.00	681.731	-24.020
139	2	1	1	1	2	1	2	1	1	13	1,755	13	1,790	13	1,870	14	1,859	14	1,840	13	1,780	13	1,644	12	1,654	13.125	13.00	757.171	-22.371
140	2	1	1	1	2	1	2	2	1	14	2,024	14	1,878	15	2,106	13	1,970	13	1,944	14	2,083	16	2,059	14	2,165	14.125	14.00	971.676	-23.018
141	2	1	1	1	2	2	1	1	1	15	1,841	15	1,740	16	1,963	16	1,773	15	1,700	16	1,932	16	1,779	16	1,880	15.625	16.00	840.153	-23.881
142	2	1	1	1	2	2	1	2	1	17	1,978	18	2,132	19	1,998	19	1,885	18	2,085	19	1,898	20	1,951	18	1,911	18.5	18.50	885.457	-25.353
143	2	1	1	1	2	2	2	1	1	15	2,294	15	2,437	15	2,393	15	2,375	15	2,257	16	2,269	16	2,425	16	2,383	15.375	15.00	1105.872	-23.741
144	2	1	1	1	2	2	2	2	1	16	2,498	16	2,440	18	2,670	18	2,565	18	2,477	19	2,490	18	2,640	16	2,446	17.375	18.00	1170.229	-24.816
145	2	1	1	2	1	1	1	1	1	14	1,360	14	1,242	14	1,388	13	1,401	13	1,325	14	1,278	13	1,296	14	1,372	13.625	14.00	611.533	-22.692
146	2	1	1	2	1	1	1	2	1	16	1,452	15	1,521	16	1,550	17	1,559	16	1,455	16	1,406	16	1,514	18	1,451	16.25	16.00	679.067	-24.228
147	2	1	1	2	1	1	2	1	1	15	2,054	13	1,871	13	1,861	14	1,942	13	1,698	14	1,988	13	1,961	13	1,816	13.5	13.00	868.744	-22.619
148	2	1	1	2	1	1	2	2	1	16	1,990	14	1,924	14	1,911	16	2,100	15	2,089	13	2,074	16	2,192	14	1,922	14.75	14.50	948.167	-23.399
149	2	1	1	2	1	2	1	1	1	16	1,722	18	1,722	16	1,871	15	1,942	17	1,934	17	1,778	18	1,929	18	1,813	16.875	17.00	859.027	-24.562
150	2	1	1	2	1	2	1	2	1	21	2,099	19	1,719	19	1,999	21	1,979	18	1,752	20	1,842	18	1,958	18	2,029	19.25	19.00	913.905	-25.705
151	2	1	1	2	1	2	2	1	1	16	2,335	16	2,358	17	2,417	15	2,347	15	2,334	18	2,364	16	2,339	20	2,471	16.625	16.00	1106.378	-24.454
152	2	1	1	2	1	2	2	2	1	25	2,627	17	2,529	19	2,637	21	2,422	23	2,644	18	2,455	15	2,526	17	2,404	19.375	18.50	1132.056	-25.859
153	2	1	1	2	2	1	1	1	1	13	1,467	12	1,250	13	1,429	14	1,341	14	1,404	13	1,275	13	1,397	13	1,453	13.125	13.00	653.723	-22.371
154	2	1	1	2	2	1	1	2	1	15	1,439	15	1,606	15	1,487	14	1,521	14	1,538	16	1,530	16	1,499	15	1,515	15	15.00	690.752	-23.531

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
155	2	1	1	2	2	1	2	1	1	13	1,820	12	1,926	12	1,843	12	1,948	12	1,900	13	1,948	13	1,872	12	1,926	12.375	12.00	873.476	-21.858
156	2	1	1	2	2	1	2	2	1	13	2,063	14	2,039	13	2,090	14	2,155	14	2,015	14	2,122	14	2,098	13	1,974	13.625	14.00	936.745	-22.692
157	2	1	1	2	2	2	1	1	1	16	1,702	17	1,989	18	1,900	17	1,809	18	1,700	16	1,749	15	1,929	15	1,656	16.5	16.50	825.129	-24.370
158	2	1	1	2	2	2	1	2	1	19	1,912	18	1,980	19	1,916	20	2,022	19	1,832	19	2,009	18	2,027	21	1,887	19.125	19.00	897.900	-25.642
159	2	1	1	2	2	2	2	1	1	16	2,358	16	2,397	14	2,395	15	2,293	17	2,495	14	2,302	17	2,630	15	2,453	15.5	15.50	1170.345	-23.829
160	2	1	1	2	2	2	2	2	1	18	2,420	18	2,595	17	2,446	17	2,434	16	2,662	16	2,533	18	2,565	18	2,488	17.25	17.50	1161.855	-24.746
161	2	1	2	1	1	1	1	1	1	13	1,313	13	1,360	14	1,303	13	1,424	13	1,266	14	1,396	14	1,340	14	1,335	13.5	13.50	612.972	-22.613
162	2	1	2	1	1	1	1	2	1	15	1,529	16	1,615	14	1,524	14	1,387	16	1,568	14	1,431	14	1,409	15	1,557	14.75	14.50	680.780	-23.390
163	2	1	2	1	1	1	2	1	1	12	2,076	13	1,976	12	1,854	12	1,906	12	1,667	12	1,922	13	1,916	13	1,828	12.375	12.00	861.257	-21.858
164	2	1	2	1	1	1	2	2	1	13	1,886	14	2,013	13	2,085	12	1,999	13	2,016	13	2,072	13	2,078	13	2,022	13	13.00	943.067	-22.285
165	2	1	2	1	1	2	1	1	1	16	1,934	18	1,950	16	1,944	15	1,810	15	1,759	18	1,810	15	1,943	16	1,787	16.125	16.00	856.782	-24.173
166	2	1	2	1	1	2	1	2	1	19	1,998	21	1,879	17	1,901	19	1,864	19	1,984	21	2,063	20	2,010	18	2,024	19.25	19.00	924.748	-25.708
167	2	1	2	1	1	2	2	1	1	15	2,253	16	2,394	14	2,168	15	2,473	15	2,431	14	2,410	17	2,453	15	2,600	15.125	15.00	1163.339	-23.610
168	2	1	2	1	1	2	2	2	1	17	2,486	19	2,712	18	2,403	18	2,544	18	2,578	18	2,640	16	2,431	18	2,542	17.75	18.00	1143.079	-24.993
169	2	1	2	1	2	1	1	1	1	14	1,444	14	1,420	13	1,422	14	1,536	14	1,307	13	1,343	14	1,299	13	1,387	13.625	14.00	615.811	-22.692
170	2	1	2	1	2	1	1	2	1	17	1,620	16	1,362	16	1,469	19	1,579	18	1,382	16	1,492	16	1,451	18	1,487	17	16.50	672.215	-24.628
171	2	1	2	1	2	1	2	1	1	13	1,866	13	1,814	13	1,865	13	1,828	13	1,978	14	1,785	13	1,794	14	1,855	13.25	13.00	838.643	-22.449
172	2	1	2	1	2	1	2	2	1	18	2,143	15	2,139	15	1,949	15	1,952	14	2,158	14	1,931	14	2,018	13	1,965	14.75	14.50	914.975	-23.414
173	2	1	2	1	2	2	1	1	1	18	1,893	17	1,855	18	1,912	18	1,842	15	1,713	16	1,896	16	1,759	16	1,851	16.75	16.50	828.049	-24.499
174	2	1	2	1	2	2	1	2	1	22	1,990	20	1,924	19	1,988	19	2,065	23	2,080	19	2,039	19	1,923	22	2,100	20.375	19.50	922.945	-26.208
175	2	1	2	1	2	2	2	1	1	17	2,476	18	2,467	18	2,514	17	2,507	16	2,295	19	2,344	16	2,287	15	2,273	17	17.00	1047.341	-24.631
176	2	1	2	1	2	2	2	2	1	22	2,729	19	2,494	18	2,395	22	2,442	19	2,446	19	2,645	23	2,505	23	2,726	20.625	20.50	1203.012	-26.326

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
177	2	1	2	2	1	1	1	1	1	14	1,479	14	1,323	14	1,401	13	1,331	13	1,284	14	1,241	13	1,266	14	1,361	13.625	14.00	602.242	-22.692
178	2	1	2	2	1	1	1	2	1	14	1,453	16	1,458	15	1,464	15	1,508	17	1,602	17	1,584	16	1,530	16	1,417	15.75	16.00	675.522	-23.962
179	2	1	2	2	1	1	2	1	1	13	1,697	13	1,916	13	1,860	13	1,809	14	1,975	14	1,784	14	1,761	13	1,881	13.375	13.00	837.402	-22.532
180	2	1	2	2	1	1	2	2	1	14	1,884	15	2,104	14	2,086	15	2,151	14	1,964	14	2,142	14	2,071	14	2,039	14.25	14.00	944.684	-23.080
181	2	1	2	2	1	2	1	1	1	19	2,003	16	1,828	16	1,735	18	1,891	16	1,710	17	1,962	17	1,756	17	1,788	17	17.00	812.453	-24.624
182	2	1	2	2	1	2	1	2	1	19	1,926	20	2,145	20	2,033	19	2,061	19	2,051	19	1,890	23	1,819	20	1,982	19.875	19.50	871.900	-25.984
183	2	1	2	2	1	2	2	1	1	17	2,463	15	2,479	16	2,455	18	2,487	16	2,569	15	2,284	16	2,536	15	2,332	16	16.00	1120.567	-24.099
184	2	1	2	2	1	2	2	2	1	16	2,406	17	2,468	15	2,426	18	2,500	18	2,548	20	2,743	16	2,440	16	2,490	17	16.50	1133.129	-24.643
185	2	1	2	2	2	1	1	1	1	13	1,403	14	1,282	15	1,376	13	1,401	14	1,470	14	1,456	13	1,255	14	1,371	13.75	14.00	602.196	-22.776
186	2	1	2	2	2	1	1	2	1	17	1,447	17	1,520	16	1,551	16	1,622	17	1,596	16	1,398	16	1,456	15	1,327	16.25	16.00	637.435	-24.224
187	2	1	2	2	2	1	2	1	1	14	2,024	13	1,779	13	1,874	13	1,846	14	2,013	13	1,796	12	1,933	13	1,888	13.125	13.00	878.300	-22.371
188	2	1	2	2	2	1	2	2	1	15	2,079	13	1,982	16	2,192	14	2,057	14	1,928	14	2,082	14	2,072	14	2,179	14.25	14.00	977.699	-23.091
189	2	1	2	2	2	2	1	1	1	17	1,873	16	1,769	15	1,639	16	1,857	18	1,810	16	1,769	18	1,836	17	1,955	16.625	16.50	870.467	-24.431
190	2	1	2	2	2	2	1	2	1	22	1,963	19	1,873	20	1,966	19	1,920	21	2,073	18	1,874	20	2,199	21	2,092	20	20.00	984.409	-26.037
191	2	1	2	2	2	2	2	1	1	16	2,643	15	2,366	14	2,398	16	2,561	17	2,625	17	2,409	15	2,399	15	2,373	15.625	15.50	1097.196	-23.894
192	2	1	2	2	2	2	2	2	1	17	2,385	18	2,476	18	2,544	16	2,566	17	2,499	17	2,557	18	2,551	21	2,511	17.75	17.50	1163.728	-25.011
193	2	2	1	1	1	1	1	1	1	13	1,398	13	1,119	14	1,176	14	1,451	14	1,395	14	1,216	14	1,333	14	1,185	13.75	14.00	577.833	-22.770
194	2	2	1	1	1	1	1	2	1	17	1,549	16	1,334	16	1,490	15	1,514	15	1,440	16	1,565	15	1,440	17	1,680	15.875	16.00	717.683	-24.025
195	2	2	1	1	1	1	2	1	1	13	1,800	13	1,898	12	1,736	13	1,875	12	1,728	13	2,001	12	1,796	12	1,834	12.5	12.50	834.380	-21.945
196	2	2	1	1	1	1	2	2	1	14	2,093	14	2,084	13	1,962	13	2,043	14	2,005	14	2,051	14	2,184	14	2,156	13.75	14.00	998.217	-22.770
197	2	2	1	1	1	2	1	1	1	18	1,866	17	1,876	17	1,902	17	1,969	17	1,790	16	1,840	16	1,834	17	1,852	16.875	17.00	845.288	-24.550
198	2	2	1	1	1	2	1	2	1	21	2,084	24	2,016	19	2,044	18	1,975	18	1,925	18	1,894	19	1,995	21	1,903	19.75	19.00	893.449	-25.955

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)…(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
199	2	2	1	1	1	2	2	1	1	16	2,362	15	2,332	17	2,291	15	2,570	14	2,405	13	2,241	14	2,385	16	2,241	15	15.00	1064.464	-23.551
200	2	2	1	1	1	2	2	2	1	17	2,591	16	2,558	19	2,610	17	2,491	17	2,550	18	2,538	18	2,527	17	2,560	17.375	17.00	1169.422	-24.809
201	2	2	1	1	2	1	1	1	1	14	1,472	15	1,329	14	1,208	14	1,277	14	1,385	14	1,266	14	1,433	14	1,243	14.125	14.00	614.916	-23.002
202	2	2	1	1	2	1	1	2	1	16	1,520	15	1,503	15	1,373	16	1,490	15	1,560	15	1,347	16	1,558	15	1,582	15.375	15.00	719.700	-23.741
203	2	2	1	1	2	1	2	1	1	14	1,829	14	2,002	12	1,949	14	1,944	12	1,786	14	1,839	13	1,893	13	1,909	13.25	13.50	873.831	-22.461
204	2	2	1	1	2	1	2	2	1	16	2,153	14	1,933	14	1,965	13	2,138	14	1,968	14	1,965	14	2,090	16	2,131	14.375	14.00	970.476	-23.173
205	2	2	1	1	2	2	1	1	1	17	1,841	18	1,952	17	1,809	17	1,812	16	1,828	17	1,871	18	1,923	16	1,692	17	17.00	831.137	-24.616
206	2	2	1	1	2	2	1	2	1	19	2,058	17	2,067	18	1,829	19	1,962	19	1,902	23	1,887	21	1,949	22	1,964	19.75	19.00	896.822	-25.952
207	2	2	1	1	2	2	2	1	1	15	2,393	17	2,445	15	2,439	15	2,336	15	2,391	15	2,451	15	2,267	16	2,521	15.375	15.00	1103.200	-23.745
208	2	2	1	1	2	2	2	2	1	18	2,466	17	2,599	19	2,420	16	2,480	19	2,608	17	2,494	18	2,542	17	2,562	17.625	17.50	1173.181	-24.936
209	2	2	1	2	1	1	1	1	1	14	1,298	14	1,431	14	1,258	14	1,312	13	1,315	14	1,239	14	1,336	14	1,273	13.875	14.00	597.700	-22.847
210	2	2	1	2	1	1	1	2	1	18	1,545	19	1,567	16	1,483	16	1,591	16	1,442	17	1,525	16	1,560	16	1,423	16.75	16.00	683.543	-24.499
211	2	2	1	2	1	1	2	1	1	14	1,988	14	1,966	15	1,767	14	1,980	14	1,961	14	1,828	14	1,800	14	1,829	14.125	14.00	833.429	-23.002
212	2	2	1	2	1	1	2	2	1	16	2,033	15	1,973	14	2,018	16	2,031	14	2,190	15	1,847	15	2,055	15	2,188	15	15.00	975.768	-23.531
213	2	2	1	2	1	2	1	1	1	17	1,744	16	1,780	16	1,987	18	1,888	18	1,853	18	1,906	16	1,845	18	1,952	17.125	17.50	871.358	-24.685
214	2	2	1	2	1	2	1	2	1	23	1,979	17	1,966	20	2,078	22	1,977	23	1,968	18	2,002	18	1,966	22	1,986	20.375	21.00	905.239	-26.236
215	2	2	1	2	1	2	2	1	1	17	2,369	17	2,426	16	2,597	16	2,301	16	2,300	16	2,467	16	2,407	18	2,277	16.5	16.00	1077.135	-24.358
216	2	2	1	2	1	2	2	2	1	20	2,694	20	2,642	19	2,470	17	2,468	19	2,453	19	2,558	20	2,516	19	2,392	19.125	19.00	1127.673	-25.642
217	2	2	1	2	2	1	1	1	1	13	1,433	13	1,341	13	1,346	13	1,371	13	1,317	13	1,317	13	1,311	13	1,414	13	13.00	625.303	-22.279
218	2	2	1	2	2	1	1	2	1	15	1,607	14	1,487	15	1,389	15	1,582	15	1,593	14	1,518	16	1,524	17	1,428	15.125	15.00	676.952	-23.610
219	2	2	1	2	2	1	2	1	1	12	1,832	13	1,997	12	1,797	12	1,912	13	1,803	13	1,759	12	1,977	12	1,911	12.375	12.00	894.285	-21.858
220	2	2	1	2	2	1	2	2	1	13	1,869	13	2,207	12	2,090	14	2,168	13	2,152	14	2,027	14	1,969	13	1,954	13.25	13.00	901.912	-22.455

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
221	2	2	1	2	2	2	1	1	1	15	1,942	16	1,914	17	1,867	15	1,784	16	1,887	16	1,739	17	1,717	18	1,822	16.25	16.00	812.275	-24.232
222	2	2	1	2	2	2	1	2	1	19	2,037	17	1,754	21	1,924	21	1,903	24	2,190	17	1,995	18	2,055	18	1,981	19.375	18.50	925.186	-25.805
223	2	2	1	2	2	2	2	1	1	16	2,486	16	2,341	15	2,451	16	2,389	15	2,336	16	2,393	15	2,280	15	2,410	15.5	15.50	1078.832	-23.811
224	2	2	1	2	2	2	2	2	1	19	2,328	19	2,474	17	2,557	16	2,407	16	2,557	18	2,504	17	2,582	16	2,433	17.25	17.00	1153.334	-24.757
225	2	2	2	1	1	1	1	1	1	13	1,344	13	1,328	14	1,403	14	1,418	14	1,340	14	1,351	13	1,279	13	1,370	13.5	13.50	607.285	-22.613
226	2	2	2	1	1	1	1	2	1	15	1,552	16	1,736	15	1,578	15	1,492	15	1,620	17	1,549	15	1,418	15	1,495	15.375	15.00	667.371	-23.745
227	2	2	2	1	1	1	2	1	1	13	1,930	12	1,807	12	1,908	12	1,853	12	1,798	12	1,805	13	1,872	12	1,872	12.25	12.00	860.936	-21.768
228	2	2	2	1	1	1	2	2	1	15	2,130	13	1,969	14	1,992	13	1,972	14	2,149	16	2,070	13	1,935	14	2,171	14	14.00	945.902	-22.945
229	2	2	2	1	1	2	1	1	1	16	2,071	18	1,836	16	1,802	15	1,771	16	1,791	15	1,719	17	1,840	16	1,841	16.125	16.00	844.580	-24.164
230	2	2	2	1	1	2	1	2	1	19	1,961	19	2,054	20	2,171	22	2,000	18	2,098	20	2,024	18	1,794	20	1,987	19.5	19.50	867.563	-25.818
231	2	2	2	1	1	2	2	1	1	15	2,404	16	2,402	14	2,393	16	2,404	16	2,446	15	2,371	15	2,531	17	2,315	15.5	15.50	1116.027	-23.820
232	2	2	2	1	1	2	2	2	1	16	2,537	18	2,640	16	2,400	17	2,453	17	2,486	16	2,576	16	2,569	17	2,521	16.625	16.50	1170.461	-24.423
233	2	2	2	1	2	1	1	1	1	14	1,344	15	1,251	14	1,330	14	1,475	15	1,430	14	1,311	14	1,332	14	1,424	14.25	14.00	631.734	-23.080
234	2	2	2	1	2	1	1	2	1	16	1,573	17	1,511	16	1,616	17	1,510	16	1,481	17	1,465	16	1,359	16	1,453	16.375	16.00	643.704	-24.287
235	2	2	2	1	2	1	2	1	1	14	1,875	14	1,705	14	1,988	14	1,877	14	1,828	14	1,785	14	1,895	14	2,023	14	14.00	901.010	-22.923
236	2	2	2	1	2	1	2	2	1	14	1,967	14	2,052	15	2,151	17	1,946	15	2,175	15	1,935	16	2,094	15	2,100	15.125	15.00	963.781	-23.610
237	2	2	2	1	2	2	1	1	1	15	1,814	19	1,787	20	1,880	17	1,829	19	2,027	18	1,831	20	1,885	19	1,845	18.375	19.00	855.063	-25.316
238	2	2	2	1	2	2	1	2	1	19	1,949	19	1,983	20	1,932	21	2,088	26	2,003	20	1,988	19	2,030	20	1,961	20.5	20.00	914.282	-26.284
239	2	2	2	1	2	2	2	1	1	15	2,317	18	2,470	17	2,275	16	2,362	17	2,385	17	2,427	18	2,374	17	2,351	16.875	17.00	1085.928	-24.558
240	2	2	2	1	2	2	2	2	1	25	2,650	19	2,411	20	2,533	18	2,682	20	2,542	19	2,454	18	2,544	21	2,428	20	19.50	1141.882	-26.069
241	2	2	2	2	1	1	1	1	1	14	1,256	14	1,326	14	1,341	14	1,327	14	1,469	13	1,419	14	1,299	13	1,399	13.75	14.00	618.640	-22.770
242	2	2	2	2	1	1	1	2	1	16	1,560	16	1,431	14	1,404	16	1,580	16	1,647	17	1,449	14	1,573	15	1,477	15.5	16.00	699.080	-23.825

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)…(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
243	2	2	2	2	1	1	2	1	1	14	1,958	13	1,867	13	1,946	14	1,937	13	1,996	13	1,915	14	1,839	13	1,972	13.375	13.00	876.624	-22.532
244	2	2	2	2	1	1	2	2	1	14	2,022	16	2,077	14	2,074	15	2,032	14	2,119	15	2,251	14	2,053	14	1,826	14.500	14.00	893.088	-23.238
245	2	2	2	2	1	2	1	1	1	18	1,815	16	1,883	17	1,937	15	1,677	18	1,818	16	1,929	18	1,812	17	1,875	16.875	17.00	845.828	-24.562
246	2	2	2	2	1	2	1	2	1	19	2,050	20	2,059	19	1,965	17	2,090	21	2,058	19	1,803	17	1,915	19	2,041	18.875	19.00	907.389	-25.537
247	2	2	2	2	1	2	2	1	1	15	2,404	16	2,391	15	2,276	15	2,301	15	2,284	15	2,424	16	2,444	9	0	14.500	15.00	859.505	-23.319
248	2	2	2	2	1	2	2	2	1	18	2,553	20	2,686	16	2,540	19	2,472	16	2,385	17	2,496	18	2,587	19	2,534	17.875	18.00	1177.189	-25.070
249	2	2	2	2	2	1	1	1	1	13	1,299	15	1,369	14	1,296	14	1,476	14	1,306	14	1,479	13	1,309	15	1,391	14.000	14.00	618.836	-22.934
250	2	2	2	2	2	1	1	2	1	15	1,520	16	1,397	16	1,378	15	1,517	15	1,451	16	1,532	15	1,379	18	1,405	15.750	15.50	637.234	-23.962
251	2	2	2	2	2	1	2	1	1	13	1,961	12	1,861	12	1,915	12	1,814	13	1,999	12	1,804	13	1,802	13	1,753	12.500	12.50	817.218	-21.945
252	2	2	2	2	2	1	2	2	1	16	2,007	13	2,034	15	2,025	15	2,226	13	1,954	15	1,929	13	2,064	14	1,972	14.250	14.50	927.767	-23.102
253	2	2	2	2	2	2	1	1	1	17	1,858	15	1,769	16	2,001	17	1,732	19	1,969	17	1,859	16	1,944	15	1,775	16.500	16.50	854.185	-24.374
254	2	2	2	2	2	2	1	2	1	21	2,058	19	2,021	20	2,038	19	1,935	18	1,961	18	1,927	21	2,036	20	2,105	19.500	19.50	949.762	-25.815
255	2	2	2	2	2	2	2	1	1	16	2,342	15	2,430	18	2,339	15	2,266	17	2,444	15	2,263	15	2,437	16	2,416	15.875	15.50	1115.859	-24.033
256	2	2	2	2	2	2	2	2	1	18	2,381	17	2,567	17	2,435	21	2,474	24	2,790	17	2,586	18	2,261	18	2,539	18.750	18.00	1104.693	-25.527
257	1	1	1	1	1	1	1	1	2	13	1,420	12.6	1,343	12.7	1,468	13.2	1,373	13.2	1,344	12.5	1,271	13.5	1,400	13.9	1,479	13.075	13.10	660.740	-22.334
258	1	1	1	1	1	1	1	2	2	13	1,386	0	0	13	1,412	12.7	1,339	12.7	1,363	12.7	1,320	12.2	1,294	12.1	1,262	11.050	12.70	586.733	-21.450
259	1	1	1	1	1	1	2	1	2	13	1,283	14.6	1,357	14.7	1,267	14.4	1,333	14.5	1,251	13.4	1,360	13.8	1,360	13.5	1,355	13.988	14.10	621.875	-22.923
260	1	1	1	1	1	1	2	2	2	15	1,456	13.9	1,367	14.5	1,350	15.2	1,454	14.6	1,274	14.5	1,439	14.3	1,313	13.5	1,289	14.438	14.50	595.514	-23.195
261	1	1	1	1	1	2	1	1	2	17	1,894	16.8	1,734	17.6	1,800	18	1,933	22.7	1,894	17.6	1,847	17.2	1,818	16	1,719	17.863	17.40	810.627	-25.088
262	1	1	1	1	1	2	1	2	2	21	2,002	18.7	1,883	22.5	1,951	25.6	1,973	28.3	1,997	35.3	2,095	32.9	2,064	20.2	2,035	25.563	24.05	937.099	-28.365
263	1	1	1	1	1	2	2	1	2	16	2,279	18.2	2,362	15.5	2,367	15.9	2,320	17.6	2,469	15.7	2,277	20.6	2,373	14.4	2,298	16.738	15.95	1073.684	-24.526
264	1	1	1	1	1	2	2	2	2	19	2,391	23.5	2,565	26.9	2,691	15.9	2,381	23.5	2,550	22.8	2,445	20	2,535	21.8	2,461	21.675	22.30	1146.371	-26.809

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
265	1	1	1	1	2	1	1	1	2	11.9	1,319	12.4	1,188	12	1,254	12.7	1,469	12.6	1,409	12.8	1,269	13.6	1,375	12.5	1,282	12.563	12.55	609.74	- 21.99
266	1	1	1	1	2	1	1	2	2	15.2	1,342	17.3	1,333	33	1,447	21.6	1,595	19.3	1,425	19	1,462	21.6	1,594	26.8	1,551	21.725	20.45	718.36	- 26.99
267	1	1	1	1	2	1	2	1	2	11.8	1,828	11.4	1,752	11.2	1,888	11.9	1,889	12.4	1,874	11.8	1,989	11.7	1,945	12.8	1,826	11.875	11.80	867.96	- 21.50
268	1	1	1	1	2	1	2	2	2	17	2,141	16.6	2,099	28.5	2,018	17.5	2,004	31.9	2,089	23.6	2,016	36.8	2,042	27.1	1,938	24.875	25.35	911.21	- 28.25
269	1	1	1	1	2	2	1	1	2	17.5	1,906	20	1,961	17.2	1,741	19.3	1,833	20	1,630	16.2	1,734	15.5	1,872	19.2	1,673	18.113	18.35	813.75	- 25.19
270	1	1	1	1	2	2	1	2	2	42.3	2,083	23.7	1,981	23.8	2,003	25.1	2,170	44.6	2,232	22.7	1,982	42.6	1,839	29.2	1,952	31.750	27.15	863.96	- 30.37
271	1	1	1	1	2	2	2	1	2	16.3	2,353	14.8	2,323	15.5	2,477	20.4	2,324	15.1	2,330	15.6	2,262	15.7	2,305	16.6	2,372	16.250	15.65	1075.13	- 24.26
272	1	1	1	1	2	2	2	2	2	19.2	2,420	25.7	2,495	25.8	2,537	21.4	2,415	19.5	2,573	22.6	2,506	22.4	2,558	28.2	2,574	23.100	22.50	1177.48	- 27.34
273	1	1	1	2	1	1	1	1	2	12	1,237	12.7	1,389	12.7	1,256	13	1,383	12.2	1,286	12.8	1,341	12.8	1,307	13.1	1,391	12.663	12.75	619.06	- 22.05
274	1	1	1	2	1	1	1	2	2	18.8	1,475	20.1	1,606	27.1	1,555	16.4	1,421	20.2	1,338	31.3	1,590	21.1	1,542	23	1,678	22.250	20.65	735.87	- 27.12
275	1	1	1	2	1	1	2	1	2	11	1,707	11.7	1,722	12.1	2,051	11.6	1,775	11.6	1,871	11.7	1,813	10.8	1,724	12	1,858	11.563	11.65	824.47	- 21.27
276	1	1	1	2	1	1	2	2	2	15.8	2,109	15.7	2,084	18.6	2,057	17.9	1,914	17.2	2,017	20.2	1,988	18.3	1,993	14.8	2,070	17.313	17.55	932.50	- 24.81
277	1	1	1	2	1	2	1	1	2	15.5	1,772	19.5	1,885	17.7	1,888	13.9	1,678	18	1,866	19.8	1,936	15.3	1,803	19.7	2,018	17.425	17.85	878.22	- 24.89
278	1	1	1	2	1	2	1	2	2	19.7	1,930	27	2,039	22.8	2,058	17.7	1,952	26.7	2,050	34.2	2,032	24.6	2,060	20.8	1,935	24.188	23.70	913.86	- 27.84
279	1	1	1	2	1	2	2	1	2	15.2	2,415	16.1	2,262	14.1	2,364	16.1	2,376	14.8	2,311	17.6	2,446	17.7	2,453	15.6	2,365	15.900	15.85	1108.16	- 24.05
280	1	1	1	2	1	2	2	2	2	19.7	2,506	25.7	2,667	14.7	2,412	21.3	2,539	17.5	2,537	21.3	2,592	17.7	2,536	18.8	2,482	19.588	19.25	1152.26	- 25.95
281	1	1	1	2	2	1	1	1	2	12.4	1,380	12.5	1,373	12.5	1,424	12.4	1,374	12.2	1,319	12.7	1,399	12.1	1,266	11.4	1,304	12.275	12.40	589.16	- 21.78
282	1	1	1	2	2	1	1	2	2	18.8	1,487	22.2	1,510	23.3	1,362	16.8	1,533	33.9	1,598	17.9	1,399	25.5	1,533	18	1,419	22.050	20.50	673.71	- 27.11
283	1	1	1	2	2	1	2	1	2	11.7	1,885	11.4	1,881	12.4	1,905	11.8	1,936	12.2	1,895	11.9	1,869	11.8	1,922	12.3	1,986	11.938	11.85	899.18	- 21.54
284	1	1	1	2	2	1	2	2	2	13.4	1,879	16.4	1,936	20.8	1,914	23.9	2,074	40.2	2,164	37.1	2,123	19	2,088	24.2	2,016	24.375	22.35	938.42	- 28.29
285	1	1	1	2	2	2	1	1	2	18.2	1,996	22.2	1,787	18.7	1,859	15.9	1,875	16.6	1,943	17.9	1,830	15.6	1,840	19.1	1,794	18.025	18.05	832.75	- 25.17
286	1	1	1	2	2	2	1	2	2	34.5	1,932	25.7	1,984	18.7	1,898	39	2,023	21.2	1,894	24.2	1,907	33.6	2,048	20.8	1,997	27.213	24.95	923.76	- 28.97

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
287	1	1	1	2	2	2	2	1	2	14.7	2,438	15.5	2,329	14.4	2,387	15.1	2,222	18.9	2,489	16	2,449	15.8	2,488	14.4	2,274	15.600	15.30	1,096.38	-23.90
288	1	1	1	2	2	2	2	2	2	18.7	2,516	23.8	2,629	19	2,462	20.3	2,458	18.5	2,374	30.4	2,688	36.4	2,584	23	2,581	23.763	21.65	1,185.39	-27.79
289	1	1	2	1	1	1	1	1	2	13.2	1,334	12.7	1,293	12.7	1,291	12	1,306	12.4	1,458	14	1,375	12.5	1,209	13.6	1,410	12.888	12.70	602.64	-22.21
290	1	1	2	1	1	1	1	2	2	19.2	1,493	25.2	1,478	16.7	1,525	22.2	1,539	23.5	1,556	18.2	1,464	21.5	1,478	20.7	1,413	20.900	21.10	659.73	-26.47
291	1	1	2	1	1	1	2	1	2	11.4	1,868	12.1	1,857	11.3	1,896	11.9	1,963	11.7	1,877	12.8	2,003	12.1	1,898	11.3	1,928	11.825	11.80	880.09	-21.46
292	1	1	2	1	1	1	2	2	2	14.7	2,058	20.1	2,042	14.2	1,946	14.8	2,164	22.1	2,191	15.2	1,903	16.7	2,040	14.4	2,044	16.525	15.00	937.47	-24.48
293	1	1	2	1	1	2	1	1	2	15.6	1,694	16.8	1,818	17.4	1,844	15.7	1,851	18.5	1,817	16.2	1,692	16.3	1,918	16.9	1,917	16.675	16.55	879.90	-24.45
294	1	1	2	1	1	2	1	2	2	24.6	1,966	27.6	2,064	19	1,895	30.6	1,926	24.6	1,988	19.8	1,919	25	2,070	21.1	2,031	24.038	24.60	937.98	-27.72
295	1	1	2	1	1	2	2	1	2	14.6	2,463	17.1	2,479	17.9	2,537	16.5	2,375	15.1	2,298	18.3	2,418	16.4	2,451	15.6	2,439	16.438	16.45	1,124.14	-24.34
296	1	1	2	1	1	2	2	2	2	22.3	2,463	23.2	2,664	19.8	2,498	18.4	2,384	19.6	2,554	19.7	2,510	17.9	2,388	19.9	2,582	20.100	19.75	1,142.02	-26.09
297	1	1	2	1	2	1	1	1	2	13.3	1,396	13.2	1,410	12.3	1,331	14.4	1,547	12.8	1,392	12.5	1,253	13.2	1,385	12.6	1,396	13.038	13.00	637.63	-22.31
298	1	1	2	1	2	1	1	2	2	17.5	1,410	54.1	1,517	25.4	1,665	46	1,494	37.5	1,560	35.2	1,495	28	1,635	24.2	1,363	33.488	31.60	681.24	-30.97
299	1	1	2	1	2	1	2	1	2	12.4	2,002	11.9	1,880	11.8	1,941	11.6	1,858	12	1,815	12.1	1,958	11.2	1,849	11.9	1,958	11.863	11.90	876.09	-21.49
300	1	1	2	1	2	1	2	2	2	17.3	1,958	17.5	2,078	17.2	1,865	14.9	1,951	29	2,087	19.1	2,155	26.7	2,054	21.9	1,959	20.450	18.30	920.32	-26.44
301	1	1	2	1	2	2	1	1	2	17.8	1,901	18.3	1,858	15.4	1,823	15	1,855	16.7	1,793	14.6	1,648	23	1,858	17.8	1,849	17.325	17.25	850.46	-24.86
302	1	1	2	1	2	2	1	2	2	17.3	1,892	29.8	1,941	26.3	1,950	21.8	2,075	27.9	2,032	22.6	1,740	16.6	1,814	33.4	1,934	24.463	24.45	856.86	-27.99
303	1	1	2	1	2	2	2	1	2	14	2,313	16.7	2,302	16.3	2,364	17.9	2,432	13.5	2,281	17.8	2,413	15.3	2,461	20.8	2,457	16.538	16.50	1,130.88	-24.45
304	1	1	2	1	2	2	2	2	2	44.9	2,712	20.6	2,610	19.6	2,461	21.8	2,504	19.6	2,548	20.9	2,584	17.5	2,413	16.3	2,414	22.650	20.10	1,105.89	-27.68
305	1	1	2	2	1	1	1	1	2	13.8	1,495	13.9	1,382	12.8	1,316	12.2	1,346	12.9	1,400	13	1,411	11.8	1,173	11.6	1,308	12.750	12.85	569.32	-22.13
306	1	1	2	2	1	1	1	2	2	16.9	1,314	19.5	1,381	23.8	1,462	16.8	1,460	20.3	1,351	18.7	1,559	18.1	1,453	18.1	1,482	19.025	18.40	670.42	-25.64
307	1	1	2	2	1	1	2	1	2	12.1	1,907	12.5	1,782	12	2,036	12.9	1,998	11.3	1,823	11.8	1,912	12.4	1,805	11.9	1,915	12.113	12.05	855.92	-21.67
308	1	1	2	2	1	1	2	2	2	23.2	1,994	20.4	2,100	14.9	2,088	17.3	1,889	14.9	1,980	17.3	1,904	29.8	2,165	17.2	2,003	19.375	17.30	957.36	-25.99

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
309	1	1	2	2	1	2	1	1	2	19.1	1,814	22.8	1,828	21.7	2,030	16.1	1,740	15.4	1,785	18.5	1,890	17.1	1,864	17.7	1,895	18.550	18.10	861.32	-25.44
310	1	1	2	2	1	2	1	2	2	19.8	1,890	20	1,933	19	1,833	20.3	1,904	26.9	2,052	22.9	2,014	40.7	2,199	31.3	2,161	25.113	21.60	999.25	-28.33
311	1	1	2	2	1	2	2	1	2	17.9	2,396	16.4	2,367	21.2	2,462	16.4	2,304	25.2	2,419	14	2,231	16.9	2,271	21.9	2,345	18.738	17.40	1,060.01	-25.60
312	1	1	2	2	1	2	2	2	2	26.3	2,515	21.1	2,494	24	2,584	21.2	2,563	22.5	2,607	23.1	2,529	22.4	2,550	24.1	2,594	23.088	22.80	1,180.00	-27.29
313	1	1	2	2	2	1	1	1	2	12.7	1,249	12.6	1,304	12.9	1,357	12.4	1,390	13.5	1,268	12.7	1,377	12.3	1,400	12.5	1,314	12.700	12.65	622.67	-22.08
314	1	1	2	2	2	1	1	2	2	17.8	1,531	31.4	1,611	28	1,531	28.2	1,496	23.6	1,525	20.8	1,534	18.2	1,410	17.6	1,440	23.200	22.20	648.15	-27.51
315	1	1	2	2	2	1	2	1	2	12	1,879	11.7	1,935	11.6	1,879	12.1	1,895	12.4	2,009	12	1,886	12.2	1,865	12.2	1,859	12.025	12.05	856.40	-21.60
316	1	1	2	2	2	1	2	2	2	35	2,229	18.6	1,952	18.8	2,017	16.8	2,085	18.3	1,966	15.4	1,852	18.3	2,033	42.5	2,176	22.963	18.45	965.49	-27.89
317	1	1	2	2	2	2	1	1	2	15.5	1,726	16.4	1,711	18.1	1,674	23.6	1,995	15.7	1,760	17	1,802	19	1,875	15.5	1,686	17.600	16.70	817.58	-25.00
318	1	1	2	2	2	2	1	2	2	23.1	1,854	35.3	2,088	27.4	2,083	18.5	1,997	23.6	1,987	53	2,142	28.2	2,012	24.3	1,992	29.175	25.85	912.87	-29.79
319	1	1	2	2	2	2	2	1	2	19.2	2,382	16	2,410	17.9	2,454	18.3	2,472	19.4	2,364	16	2,242	14.9	2,368	17	2,387	17.338	17.45	1,092.34	-24.81
320	1	1	2	2	2	2	2	2	2	19.5	2,412	27.3	2,405	23.7	2,486	41.8	2,750	50.3	2,906	31.7	2,569	26.1	2,492	20.3	2,564	30.088	26.70	1,155.45	-30.03
321	1	2	1	1	1	1	1	1	2	13.2	1,272	13.5	1,373	12.6	1,455	13.1	1,376	13	1,421	13.5	1,498	12.8	1,398	12.4	1,359	13.013	13.05	632.12	-22.29
322	1	2	1	1	1	1	1	2	2	25.2	1,534	18.1	1,540	17.1	1,530	20.6	1,492	19.7	1,551	23.3	1,478	27.3	1,614	16.5	1,391	20.975	20.15	688.54	-26.57
323	1	2	1	1	1	1	2	1	2	13.1	2,006	12.5	1,878	12.4	1,874	12.8	1,984	12.3	1,922	12.6	1,994	12.1	1,897	12	1,976	12.475	12.45	890.84	-21.92
324	1	2	1	1	1	1	2	2	2	13.4	1,903	21.4	2,038	17.6	2,069	16.4	2,104	20.6	2,024	17.9	2,139	21.5	2,179	18.3	2,041	18.388	18.10	969.17	-25.38
325	1	2	1	1	1	2	1	1	2	17.8	1,848	16.4	1,906	16.7	1,745	19.9	1,951	15.2	1,677	20.3	1,841	17.4	1,699	19.5	1,808	17.900	17.60	804.04	-25.10
326	1	2	1	1	1	2	1	2	2	20.5	2,011	25.6	1,911	19.9	1,982	24.6	1,894	19.7	1,927	17.7	1,838	27.2	2,056	24.4	1,962	22.450	22.45	920.46	-27.11
327	1	2	1	1	1	2	2	1	2	19.1	2,367	16.2	2,417	16.5	2,499	17.8	2,346	17.3	2,355	16.5	2,327	17	2,311	15.7	2,275	17.013	16.75	1,053.52	-24.63
328	1	2	1	1	1	2	2	2	2	23.7	2,530	17.7	2,284	19.3	2,480	23.8	2,421	19.6	2,405	23.3	2,615	22.4	2,550	24.1	2,634	21.738	22.85	1,190.25	-26.79
329	1	2	1	1	2	1	1	1	2	12.3	1,370	12.6	1,330	13.6	1,447	12.7	1,250	12.5	1,279	13.7	1,244	13.2	1,286	12.4	1,418	12.875	12.65	620.89	-22.20
330	1	2	1	1	2	1	1	2	2	19.4	1,412	22.8	1,554	24.5	1,384	25.5	1,439	23.6	1,549	20.7	1,625	16.9	1,526	19.7	1,418	21.638	21.75	671.50	-26.77

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)…(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
331	1	2	1	1	2	1	2	1	2	12	1,830	11.7	1,868	12.3	1,943	11.8	1,838	12.7	1,907	12.3	1,956	11.7	1,814	12.9	1,824	12.175	12.15	836.42	-21.71
332	1	2	1	1	2	1	2	2	2	16.2	2,012	17.3	2,066	15.5	1,967	19.1	2,017	22.7	2,064	15.5	2,053	21.8	1,995	15.7	2,031	17.975	16.75	923.69	-25.19
333	1	2	1	1	2	2	1	1	2	20.9	1,784	20	1,805	17.7	1,748	15.6	1,707	19.9	1,982	21.1	2,009	15.4	1,811	18	1,820	18.575	18.95	831.53	-25.43
334	1	2	1	1	2	2	1	2	2	32.9	1,982	32.6	2,106	28.6	1,969	29.4	1,809	20.8	1,860	34.9	2,023	19.1	1,828	30.6	1,926	28.613	30.00	855.47	-29.28
335	1	2	1	1	2	2	2	1	2	18.6	2,411	16.4	2,314	16.7	2,395	18.2	2,245	17	2,291	18.6	2,506	22.7	2,371	21.4	2,552	18.700	18.40	1,132.35	-25.49
336	1	2	1	1	2	2	2	2	2	23.8	2,586	24.3	2,584	22.5	2,409	32.8	2,635	24.7	2,585	18.3	2,503	22.8	2,597	27	2,491	24.525	24.05	1,166.70	-27.90
337	1	2	1	2	1	1	1	1	2	12.2	1,318	13.2	1,392	13.2	1,398	12.9	1,435	12.7	1,234	13.2	1,294	12.2	1,162	13.1	1,414	12.838	13.00	594.09	-22.17
338	1	2	1	2	1	1	1	2	2	17.9	1,473	15.3	1,398	17.9	1,511	19.2	1,504	19.2	1,513	18.9	1,455	26.1	1,501	18.9	1,561	19.175	18.90	700.54	-25.75
339	1	2	1	2	1	1	2	1	2	11.8	1,890	11.7	1,777	11.7	1,886	12	1,932	12	1,797	11.4	1,727	12	1,816	11.2	1,767	11.725	11.75	823.96	-21.38
340	1	2	1	2	1	1	2	2	2	15.3	1,938	21.9	2,114	15	2,057	14.5	1,949	17.5	2,024	21.6	1,921	19.1	2,057	16.4	1,904	17.663	16.95	909.55	-25.04
341	1	2	1	2	1	2	1	1	2	17.8	1,883	16.6	1,697	15.1	1,628	16.7	1,848	15.8	1,850	16.8	1,835	17.2	1,868	21.1	1,842	17.138	16.75	851.10	-24.72
342	1	2	1	2	1	2	1	2	2	28.6	1,868	28.2	2,041	24.4	2,038	26.1	2,021	19.9	1,876	17.4	1,853	27.8	2,111	20.8	1,878	24.150	25.25	914.25	-27.78
343	1	2	1	2	1	2	2	1	2	17.7	2,357	14.8	2,431	13.8	2,260	17.7	2,276	15.7	2,278	15.4	2,448	14.5	2,281	17.1	2,241	15.838	15.55	1,039.36	-24.03
344	1	2	1	2	1	2	2	2	2	19.2	2,581	19.6	2,643	23.8	2,567	24.3	2,466	18.3	2,593	26.1	2,656	17.7	2,556	19	2,476	21.000	19.40	1,154.75	-26.53
345	1	2	1	2	2	1	1	1	2	13	1,351	12.9	1,323	13.3	1,418	13	1,382	12.5	1,326	12.7	1,261	12.5	1,291	11.9	1,224	12.725	12.80	576.42	-22.10
346	1	2	1	2	2	1	1	2	2	22.9	1,410	20.5	1,450	17.2	1,494	21.9	1,425	24.5	1,423	16.6	1,304	35.3	1,654	16.6	1,556	21.938	21.20	733.91	-27.12
347	1	2	1	2	2	1	2	1	2	12.6	2,020	12.3	1,913	12.1	1,959	11.9	1,895	12.3	1,949	12.4	1,939	12.8	1,946	12.6	1,946	12.375	12.35	895.14	-21.85
348	1	2	1	2	2	1	2	2	2	29.1	2,096	19.1	1,899	17.8	2,070	21.9	2,086	24.8	2,063	33.5	2,161	23.1	2,031	31.1	2,071	25.050	23.95	938.22	-28.17
349	1	2	1	2	2	2	1	1	2	21.2	1,976	17.5	1,690	19.3	1,842	15.7	1,849	17.2	1,882	16.2	1,796	16.5	1,780	15.6	1,840	17.400	16.85	829.76	-24.86
350	1	2	1	2	2	2	1	2	2	32.1	2,098	29.1	2,057	24.2	1,947	22.6	1,944	42.2	2,222	23.5	2,040	30.3	2,073	20.3	1,833	28.038	26.65	892.99	-29.19
351	1	2	1	2	2	2	2	1	2	14.8	2,267	17.8	2,458	16.3	2,453	17.7	2,546	15.7	2,362	17.9	2,483	14.5	2,316	14.7	2,272	16.175	16.00	1,054.25	-24.21
352	1	2	1	2	2	2	2	2	2	20.6	2,465	18	2,443	25.5	2,592	17.9	2,517	20	2,530	23.5	2,446	30.7	2,537	27.5	2,628	22.963	22.05	1,186.03	-27.37

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
353	1	2	2	1	1	1	1	1	2	11.9	1,211	12.3	1,388	13.6	1,265	12.9	1,403	12.9	1,420	12.9	1,350	12.4	1,310	13.2	1,439	12.763	12.90	631.31	-22.13
354	1	2	2	1	1	1	1	2	2	26.9	1,552	18.2	1,453	23.8	1,581	25.4	1,473	16.1	1,472	21.9	1,539	18.4	1,609	15.2	1,329	20.738	20.15	673.98	-26.50
355	1	2	2	1	1	1	2	1	2	11.7	1,928	12.3	1,823	12.2	2,047	12.2	1,912	12.5	2,061	12	1,859	12.6	1,864	12.8	1,953	12.288	12.25	878.16	-21.79
356	1	2	2	1	1	1	2	2	2	18.2	2,190	14.1	1,969	23.4	2,074	16.7	2,034	14.4	1,983	22.3	2,154	31	2,154	16.2	1,979	19.538	17.45	949.35	-26.13
357	1	2	2	1	1	2	1	1	2	19.1	1,817	16.3	1,791	22.6	1,794	16.8	1,847	14.7	1,724	22.5	1,859	17	1,887	18.6	1,806	18.450	17.80	846.40	-25.41
358	1	2	2	1	1	2	1	2	2	25.4	2,018	23.8	2,059	22.8	2,122	22.8	2,013	18.3	1,882	32	2,099	17.5	1,790	29.1	1,989	23.963	23.30	865.12	-27.75
359	1	2	2	1	1	2	2	1	2	16.1	2,340	17.7	2,420	15.9	2,430	15.6	2,294	17.2	2,503	15.2	2,302	20.7	2,495	18.5	2,488	17.113	16.65	1,145.80	-24.71
360	1	2	2	1	1	2	2	2	2	17.6	2,381	31.7	2,781	20.3	2,507	26.4	2,531	19	2,403	22	2,624	25.3	2,626	17.3	2,526	22.450	21.15	1,182.20	-27.21
361	1	2	2	1	2	1	1	1	2	13.5	1,494	12.7	1,326	13.5	1,250	13.4	1,321	12.5	1,204	12.9	1,353	12.6	1,308	12.4	1,332	12.938	12.80	605.02	-22.24
362	1	2	2	1	2	1	1	2	2	21.1	1,505	20.5	1,559	18.4	1,553	17.9	1,496	21.9	1,419	16.9	1,483	35.7	1,487	20.9	1,390	21.663	20.70	657.41	-26.99
363	1	2	2	1	2	1	2	1	2	11.7	1,802	11.8	1,798	12.6	1,909	12.2	1,816	12.7	1,814	11.7	1,959	11.6	1,947	12.1	1,697	12.050	11.95	840.47	-21.62
364	1	2	2	1	2	1	2	2	2	22.7	2,047	18.3	1,994	17.7	2,099	14.8	1,794	22.5	2,057	29.5	2,070	23.5	2,075	21.5	1,931	21.313	22.00	918.34	-26.74
365	1	2	2	1	2	2	1	1	2	14.8	1,795	16.1	1,862	18.2	1,939	24.7	1,725	15.4	1,788	17.2	1,748	17.6	1,753	15.5	1,739	17.438	16.65	800.05	-24.95
366	1	2	2	1	2	2	1	2	2	44.2	2,113	20.1	1,859	35.3	1,960	28.2	1,934	26.5	1,990	31	2,083	34.7	1,982	19.9	1,898	29.988	29.60	884.06	-29.81
367	1	2	2	1	2	2	2	1	2	16.4	2,307	15.1	2,239	22	2,480	21.8	2,341	16.8	2,424	16.2	2,404	14.9	2,234	15.1	2,167	17.288	16.30	1,010.44	-24.86
368	1	2	2	1	2	2	2	2	2	16.7	2,535	19.1	2,555	15.6	2,414	21.9	2,543	36.4	2,545	22.3	2,479	23.6	2,427	22.5	2,656	22.263	22.10	1,167.92	-27.26
369	1	2	2	2	1	1	1	1	2	13.2	1,372	13	1,393	12.4	1,335	13.5	1,411	12.3	1,346	13.5	1,559	13.4	1,342	13.9	1,387	13.150	13.30	625.75	-22.39
370	1	2	2	2	1	1	1	2	2	19	1,516	20.7	1,496	23	1,454	18.9	1,420	34.8	1,568	16.5	1,447	15.6	1,332	21.8	1,542	21.288	19.85	657.37	-26.85
371	1	2	2	2	1	1	2	1	2	12.1	1,863	13.5	1,967	12.6	2,061	12.3	1,941	12	1,800	13.1	1,851	11.9	1,835	12.1	1,811	12.450	12.20	838.08	-21.91
372	1	2	2	2	1	1	2	2	2	17.9	1,996	15.4	2,084	22	2,061	14.5	1,926	15.2	1,878	20.3	2,071	15.7	2,045	15.8	2,009	17.100	15.75	930.25	-24.76
373	1	2	2	2	1	2	1	1	2	17.4	1,813	16.7	1,672	21.9	1,865	16.7	1,843	20.5	1,795	16.7	1,826	18.2	1,818	15.1	1,803	17.900	17.05	829.63	-25.12
374	1	2	2	2	1	2	1	2	2	21.5	1,938	17.6	1,819	28.3	2,045	24.4	2,035	35.3	2,066	21.8	1,950	24.3	2,078	24.3	2,078	24.688	24.30	950.45	-28.02

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued).

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
375	1	2	2	2	1	2	2	1	2	15.9	2,212	28.4	2,609	26.3	2,509	17.7	2,264	16.6	2,272	16.1	2,293	16.9	2,374	19.6	2,343	19.688	17.30	1,082.48	-26.11
376	1	2	2	2	1	2	2	2	2	22.2	2,632	22.2	2,465	22.6	2,442	20.2	2,401	23.9	2,502	25.4	2,551	18.9	2,387	22.5	2,616	22.238	22.35	1,149.07	-26.97
377	1	2	2	2	2	1	1	1	2	13.2	1,372	13.3	1,344	11.5	1,321	12.4	1,241	13.6	1,466	12.7	1,369	12.1	1,226	12.6	1,263	12.675	12.65	570.26	-22.07
378	1	2	2	2	2	1	1	2	2	17.1	1,392	37.5	1,420	21.3	1,591	38.3	1,624	42.7	1,592	30	1,541	27.4	1,590	31.2	1,474	30.688	30.60	695.50	-30.04
379	1	2	2	2	2	1	2	1	2	11.9	1,852	13.4	1,992	12.1	1,914	13	1,916	11.5	1,799	12.6	1,882	11.6	1,747	12.1	1,868	12.275	12.10	831.59	-21.79
380	1	2	2	2	2	1	2	2	2	20.8	2,021	27.3	2,057	25.9	2,076	28.6	2,130	18	1,940	16.6	2,059	15.1	1,808	16.6	1,971	21.113	19.40	865.19	-26.73
381	1	2	2	2	2	2	1	1	2	15	1,808	20.1	1,872	17.8	1,852	17.5	1,758	21.7	1,805	19.5	1,880	17.4	1,819	21.5	1,837	18.813	18.65	837.61	-25.55
382	1	2	2	2	2	2	1	2	2	36.3	2,029	45.4	2,027	24.6	2,065	19.2	1,774	19.4	2,024	19	1,865	20.8	1,936	29.9	2,181	26.825	22.70	942.58	-29.04
383	1	2	2	2	2	2	2	1	2	15.7	2,353	15.7	2,204	18.6	2,483	19.9	2,357	21.9	2,472	15.8	2,356	18.8	2,486	20.2	2,536	18.325	18.70	1,154.15	-25.32
384	1	2	2	2	2	2	2	2	2	22.4	2,630	21.7	2,472	28.7	2,414	22.9	2,444	32.8	2,595	24.3	2,473	31.1	2,560	20.7	2,472	25.575	23.60	1,153.14	-28.28
385	2	1	1	1	1	1	1	1	2	15.1	1,276	12.6	1,207	15.3	1,282	13.2	1,376	14.2	1,367	13.4	1,347	15.9	1,336	14.4	1,295	14.263	14.30	602.59	-23.11
386	2	1	1	1	1	1	1	2	2	33.8	1,464	31.7	1,431	26.9	1,569	37.6	1,439	35.4	1,477	32.9	1,491	37.6	1,438	28.6	1,605	33.063	33.35	690.47	-30.44
387	2	1	1	1	1	1	2	1	2	12.7	1,743	14.2	1,894	13.5	1,905	12	1,728	16.6	1,956	12.3	1,958	14.5	1,894	13.2	1,695	13.625	13.35	826.13	-22.73
388	2	1	1	1	1	1	2	2	2	23.8	1,957	22.2	1,964	28.7	1,960	27.9	2,064	42.5	2,146	31.4	1,988	23.6	2,015	31	2,049	28.888	28.30	927.08	-29.40
389	2	1	1	1	1	2	1	1	2	28.7	1,809	24.3	1,725	29.7	1,810	29	1,847	24.8	1,747	27.3	1,810	18.4	1,747	29.3	1,574	26.438	28.00	757.44	-28.52
390	2	1	1	1	1	2	1	2	2	35.2	1,964	57.4	1,898	56.3	1,960	54.2	2,032	36.9	1,792	41	1,929	42.8	1,856	46.1	1,809	46.238	44.45	826.74	-33.43
391	2	1	1	1	1	2	2	1	2	22.5	2,221	21.4	2,173	20.9	2,383	27.8	2,395	25.9	2,274	30.9	2,362	24.5	2,152	28	2,299	25.238	25.20	1,019.44	-28.12
392	2	1	1	1	1	2	2	2	2	37.9	2,350	35.1	2,485	34.3	2,511	42.8	2,447	34.2	2,532	42.5	2,498	36.2	2,482	41.2	2,371	38.025	37.05	1,106.16	-31.64
393	2	1	1	1	2	1	1	1	2	13.2	1,320	15.4	1,296	14.5	1,327	13.3	1,317	14.9	1,363	13.6	1,250	14.1	1,283	14.5	1,302	14.188	14.30	591.78	-23.05
394	2	1	1	1	2	1	1	2	2	51.4	1,508	48.9	1,575	53.6	1,530	43	1,402	51	1,458	50.2	1,474	63.1	1,453	42.6	1,422	50.475	50.60	642.49	-34.12
395	2	1	1	1	2	1	2	1	2	14.6	1,949	15.7	1,910	13.7	1,841	13.8	1,884	14.4	2,025	13.1	1,782	14.1	1,886	14.8	1,884	14.275	14.25	866.00	-23.10
396	2	1	1	1	2	1	2	2	2	32.4	2,010	38.9	1,955	45.5	2,128	42.7	2,104	35.5	2,041	46.7	1,983	41.1	2,016	36.3	1,977	39.888	40.00	905.63	-32.08

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued)

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
397	2	1	1	1	2	2	1	1	2	28.6	1,725	30.8	1,904	23.7	1,602	30.2	1,934	27.7	1,853	29.4	1,814	25.9	1,642	30.9	1,994	28.400	29.00	833.75	-29.10
398	2	1	1	1	2	2	1	2	2	49.6	1,904	50.8	1,838	53.1	1,872	63.3	1,944	48.1	2,052	61.7	2,040	47.9	1,854	51.2	2,090	53.213	51.00	889.92	-34.57
399	2	1	1	1	2	2	2	1	2	24.7	2,399	23.4	2,145	25.8	2,285	31.8	2,221	31.3	2,310	22.2	2,293	24.9	2,234	25.9	2,168	26.250	25.35	1,006.74	-28.45
400	2	1	1	1	2	2	2	2	2	56.6	2,615	39	2,317	60.3	2,584	46.4	2,515	41.9	2,410	39.9	2,415	42.2	2,374	41.3	2,426	45.950	42.05	1,089.18	-33.36
401	2	1	1	2	1	1	1	1	2	13.2	1,262	14.8	1,324	14.7	1,395	14.5	1,374	13.3	1,372	13.6	1,301	13	1,384	13.8	1,291	13.863	13.70	613.16	-22.85
402	2	1	1	2	1	1	1	2	2	23.2	1,278	31.6	1,534	24.4	1,448	27.5	1,469	29.9	1,456	27.9	1,427	31.6	1,351	23.9	1,458	27.500	27.70	638.11	-28.84
403	2	1	1	2	1	1	2	1	2	11.9	1,934	13.2	1,956	14.1	2,006	14.4	1,906	13.8	2,017	14.4	1,840	14.3	1,794	16.3	1,774	14.050	14.20	819.54	-22.98
404	2	1	1	2	1	1	2	2	2	19.6	1,775	29.3	2,137	28.2	1,941	25.5	2,040	28.1	2,046	30.6	2,051	21.9	1,974	28.2	1,922	26.425	28.15	889.42	-28.52
405	2	1	1	2	1	2	1	1	2	24.8	1,761	21.1	1,679	23	1,788	23	1,748	22.5	1,781	19.9	1,784	20.7	1,683	21.7	1,865	22.088	22.10	812.30	-26.90
406	2	1	1	2	1	2	1	2	2	49.7	2,064	47.9	2,073	39.4	1,947	41	1,969	46.3	2,018	30.1	1,809	42.1	1,911	51.2	2,022	43.463	44.20	891.20	-32.86
407	2	1	1	2	1	2	2	1	2	23.4	2,518	26.2	2,501	24.7	2,378	16.9	2,181	26.9	2,417	24.5	2,225	24.1	2,495	24.7	2,362	23.925	24.60	1,113.75	-27.64
408	2	1	1	2	1	2	2	2	2	28.1	2,392	33.6	2,558	30.2	2,450	36.3	2,600	35.5	2,367	28.4	2,538	32.7	2,608	38.5	2,630	32.913	33.15	1,197.56	-30.40
409	2	1	1	2	2	1	1	1	2	12.9	1,254	13.2	1,343	13.4	1,332	13.2	1,325	14	1,380	15.1	1,441	13.4	1,335	14.8	1,338	13.750	13.40	612.37	-22.78
410	2	1	1	2	2	1	1	2	2	53.4	1,541	52.8	1,509	55.6	1,495	57.7	1,443	60.9	1,505	35.6	1,332	56	1,440	45.5	1,462	52.188	54.50	647.37	-34.44
411	2	1	1	2	2	1	2	1	2	13.8	1,857	13.7	1,923	13.9	1,846	14.2	1,921	14.2	1,755	14	1,955	12.4	1,813	14.8	1,843	13.875	13.95	839.77	-22.85
412	2	1	1	2	2	1	2	2	2	22.9	1,893	36.9	2,021	49.5	2,110	33.6	2,055	45.1	2,154	42	2,061	40.8	1,978	48.5	1,995	39.913	41.40	901.87	-32.20
413	2	1	1	2	2	2	1	1	2	23.3	1,837	24.4	1,886	21.6	1,835	24.4	1,715	24.8	1,960	22.7	1,776	20.7	1,654	24.7	1,805	23.325	23.85	790.74	-27.37
414	2	1	1	2	2	2	1	2	2	54.4	2,004	62.5	2,090	55.3	2,018	52.1	1,962	59.7	1,912	49.5	1,886	34.4	1,802	48.7	1,861	52.075	53.25	822.25	-34.43
415	2	1	1	2	2	2	2	1	2	27	2,383	23.5	2,450	23.9	2,383	25.7	2,508	23	2,266	28.6	2,405	20	2,174	21.4	2,441	24.138	23.70	1,058.87	-27.71
416	2	1	1	2	2	2	2	2	2	50.2	2,553	49.6	2,539	49.7	2,519	51.2	2,538	51.6	2,550	52.3	2,554	45.6	2,465	43	2,413	49.150	49.95	1,105.62	-33.85
417	2	1	2	1	1	1	1	1	2	13.2	1,198	14.5	1,270	13	1,246	12.6	1,228	13.8	1,335	13.4	1,164	14	1,421	12.9	1,389	13.425	13.30	644.23	-22.57
418	2	1	2	1	1	1	1	2	2	40.7	1,569	33	1,400	30.4	1,383	21.3	1,500	47.6	1,513	36.6	1,450	22.8	1,385	28	1,462	32.550	31.70	643.16	-30.53

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued)

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
419	2	1	2	1	1	1	2	1	2	13.5	1,937	13.4	1,851	15.9	2,021	13.3	1,877	13.2	1,944	13.4	1,930	12.6	1,722	12.8	1,946	13.513	13.35	844.72	-22.64
420	2	1	2	1	1	1	2	2	2	32.1	2,052	24.6	2,051	22.7	1,999	33.2	1,932	24.4	1,757	30.8	1,945	33.4	1,976	29.1	1,913	28.788	29.95	887.35	-29.27
421	2	1	2	1	1	2	1	1	2	27.9	1,840	31.3	1,723	25.4	1,722	30.7	1,856	35	1,880	30.4	1,847	26.1	1,935	26.7	1,749	29.188	29.15	840.22	-29.35
422	2	1	2	1	1	2	1	2	2	31.2	1,720	33.9	1,912	37.3	1,980	42.8	1,924	44	2,008	39.2	2,025	45	1,895	39.3	2,039	39.088	39.25	893.76	-31.90
423	2	1	2	1	1	2	2	1	2	26.2	2,417	25.6	2,217	27.4	2,226	28.3	2,360	22.7	2,231	25.5	2,453	26.8	2,369	24.1	2,358	25.825	25.90	1,082.08	-28.26
424	2	1	2	1	1	2	2	2	2	41.8	2,503	36.3	2,407	45	2,544	32.8	2,455	33.7	2,408	44.2	2,517	34.6	2,544	35	2,459	37.925	35.65	1,140.17	-31.64
425	2	1	2	1	2	1	1	1	2	13.6	1,276	15	1,483	15.4	1,354	14	1,399	13.8	1,283	12.9	1,307	13.3	1,365	14.8	1,336	14.100	13.90	618.67	-23.00
426	2	1	2	1	2	1	1	2	2	47.3	1,440	54.3	1,491	63.5	1,502	52.4	1,393	60.5	1,491	58.3	1,631	50.5	1,486	57.4	1,495	55.525	55.85	664.04	-34.93
427	2	1	2	1	2	1	2	1	2	12.3	1,818	13.9	1,983	13.7	1,921	13.3	1,841	12.8	1,813	13.6	1,870	14.8	2,052	13.8	1,907	13.525	13.65	911.01	-22.63
428	2	1	2	1	2	1	2	2	2	41.9	1,992	37.5	1,989	41.6	1,830	24.6	1,902	44.7	2,034	40.6	2,010	42.2	2,024	39.6	1,973	39.088	41.10	907.43	-31.94
429	2	1	2	1	2	2	1	1	2	29.3	2,011	25.2	1,899	27.8	1,810	28.3	1,875	31.6	1,964	22	1,838	25.9	1,888	29.4	1,824	27.438	28.05	846.67	-28.81
430	2	1	2	1	2	2	1	2	2	57.3	1,936	49.1	1,954	52.6	1,900	63	1,935	67.9	1,983	60.4	1,967	41.1	1,937	50.7	1,894	55.263	54.95	859.77	-34.94
431	2	1	2	1	2	2	2	1	2	24.1	2,251	27.2	2,386	27.3	2,444	25.2	2,388	24.6	2,363	23.4	2,370	25.7	2,306	26.9	2,388	25.550	25.45	1,074.96	-28.16
432	2	1	2	1	2	2	2	2	2	52.9	2,554	56.5	2,639	58.8	2,685	44.2	2,495	54	2,560	49.6	2,523	55	2,518	45.1	2,517	52.013	53.45	1,141.00	-34.36
433	2	1	2	2	1	1	1	1	2	14.8	1,475	13.1	1,301	15.7	1,474	15.2	1,307	14.1	1,305	14.8	1,361	13.5	1,290	13.3	1,323	14.313	14.45	598.09	-23.13
434	2	1	2	2	1	1	1	2	2	26.1	1,501	41.6	1,529	22.7	1,369	36.9	1,505	31	1,551	36.9	1,476	38.3	1,578	25.8	1,414	32.413	33.95	678.90	-30.39
435	2	1	2	2	1	1	2	1	2	12.7	1,803	13.1	1,803	12.9	1,834	13.5	1,868	13.8	1,693	12.4	1,699	12.9	1,820	16.1	1,947	13.425	13.00	866.51	-22.59
436	2	1	2	2	1	1	2	2	2	23.8	1,940	27.7	1,909	26.8	2,121	22	2,159	29.5	2,026	27.1	1,943	30	1,972	33.4	1,874	27.538	27.40	878.46	-28.86
437	2	1	2	2	1	2	1	1	2	30.8	1,879	27.8	1,779	30.4	1,717	30.8	1,913	25.2	1,762	29.4	1,858	29.4	1,919	29.5	1,807	29.163	29.45	849.48	-29.31
438	2	1	2	2	1	2	1	2	2	35.9	1,851	43.6	1,868	39.6	1,912	42.2	2,036	45.7	2,092	38.5	1,748	32.5	1,853	51.3	1,928	41.163	40.90	856.43	-32.37
439	2	1	2	2	1	2	2	1	2	24.2	2,365	27.6	2,304	31	2,465	27.2	2,375	28.6	2,316	32.6	2,267	30	2,377	28.1	2,228	28.663	28.35	1,053.40	-29.18
440	2	1	2	2	1	2	2	2	2	35.4	2,428	40.8	2,566	42.3	2,475	34.5	2,363	36.4	2,466	40.3	2,646	38.8	2,533	41.5	2,603	38.750	39.55	1,171.18	-31.79

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued)

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
441	2	1	2	2	2	1	1	1	2	12.8	1,188	14.4	1,362	13.3	1,326	14.5	1,457	15	1,385	17.4	1,345	14.1	1,360	12.7	1,395	14.275	14.25	630.99	-23.13
442	2	1	2	2	2	1	1	2	2	45	1,314	60.5	1,545	51.6	1,559	50.5	1,535	57	1,510	60	1,636	60.4	1,587	68.2	1,453	56.650	58.50	679.54	-35.13
443	2	1	2	2	2	1	2	1	2	14.5	1,808	13.2	1,844	12.8	1,983	13.4	1,894	14.2	1,844	13	1,924	14.7	1,868	14.8	1,844	13.825	13.80	852.93	-22.83
444	2	1	2	2	2	1	2	2	2	45.3	2,015	54.6	2,097	48.7	2,190	42.1	1,991	49.1	2,054	41.8	1,974	40.6	1,948	44.6	2,050	45.850	44.95	904.05	-33.27
445	2	1	2	2	2	2	1	1	2	25.5	1,694	30.3	1,919	30.3	1,753	31	1,736	27.5	1,882	31.7	1,956	32.7	1,863	32.1	1,943	30.138	30.65	867.58	-29.61
446	2	1	2	2	2	2	1	2	2	36.2	1,741	61.2	1,944	37.4	2,000	62.2	2,039	47.6	1,884	48.2	1,854	50	1,809	61.4	1,978	50.525	49.10	855.18	-34.23
447	2	1	2	2	2	2	2	1	2	25.9	2,375	29.3	2,480	27	2,386	32.5	2,417	28.4	2,221	27.9	2,323	27.6	2,582	30.6	2,264	28.650	28.15	1,111.69	-29.16
448	2	1	2	2	2	2	2	2	2	32.7	2,413	47.5	2,399	48.1	2,462	55	2,558	58.8	2,603	48.5	2,466	57.6	2,590	52.2	2,506	50.050	50.35	1,157.32	-34.09
449	2	2	1	1	1	1	1	1	2	13.3	1,381	14.3	1,415	13.9	1,291	15.3	1,391	14.8	1,271	16.1	1,400	14.6	1,440	14.2	1,341	14.563	14.45	637.46	-23.28
450	2	2	1	1	1	1	1	2	2	46.9	1,553	23.6	1,422	25.8	1,455	39.9	1,444	44.1	1,481	29.8	1,490	43	1,513	42.3	1,482	36.925	41.10	677.10	-31.57
451	2	2	1	1	1	1	2	1	2	14.1	1,930	13.4	1,833	14.8	1,837	13.9	1,746	16.4	1,924	15.1	1,732	11.9	1,729	13	1,751	14.075	14.00	798.72	-23.01
452	2	2	1	1	1	1	2	2	2	31.6	1,961	25	1,743	31.1	2,118	23.4	2,025	21.7	1,886	27.1	1,817	23.4	1,936	35.3	2,027	27.325	26.05	905.25	-28.85
453	2	2	1	1	1	2	1	1	2	21.2	1,750	25.7	1,614	25.8	1,699	26.3	1,829	26.6	1,859	26.4	1,876	23.6	1,840	21.1	1,775	24.588	25.75	825.17	-27.85
454	2	2	1	1	1	2	1	2	2	37.8	1,839	40.9	1,975	32.5	1,928	41.4	1,913	47.3	1,876	36.7	1,855	37.4	1,881	40.4	1,902	39.300	39.10	857.37	-31.93
455	2	2	1	1	1	2	2	1	2	19.7	2,206	27.1	2,275	26.3	2,373	26.1	2,322	27.1	2,468	24.6	2,313	27.4	2,249	28.5	2,399	25.850	26.70	1,064.92	-28.29
456	2	2	1	1	1	2	2	2	2	35.2	2,448	31.3	2,305	34	2,480	32.4	2,413	47.7	2,554	36	2,531	39.8	2,349	42.5	2,522	37.363	35.60	1,111.68	-31.53
457	2	2	1	1	2	1	1	1	2	15.3	1,341	13.4	1,225	14.3	1,278	13.5	1,266	13.6	1,297	15.1	1,211	13.7	1,291	14.9	1,281	14.225	14.00	588.74	-23.07
458	2	2	1	1	2	1	1	2	2	50.3	1,439	51.9	1,330	54.1	1,394	55.1	1,655	52.1	1,474	33.3	1,285	47.2	1,416	50.9	1,485	49.363	51.40	648.85	-33.94
459	2	2	1	1	2	1	2	1	2	14.8	1,869	13.2	1,727	14.8	1,910	13	1,748	13.1	1,786	13.9	1,697	14.1	1,839	15.9	1,912	14.100	14.00	862.02	-23.00
460	2	2	1	1	2	1	2	2	2	39.3	1,993	42.2	1,969	42.3	1,909	45.6	2,095	45.8	1,997	52.7	1,962	42.8	2,111	43.8	1,956	44.313	43.30	921.60	-32.96
461	2	2	1	1	2	2	1	1	2	27.9	1,784	27.1	1,844	27.5	1,912	28.1	1,691	25.4	1,823	26	1,793	19.6	1,752	24.5	1,751	25.763	26.55	798.29	-28.26
462	2	2	1	1	2	2	1	2	2	67.2	2,067	44.3	1,934	61.1	2,118	59.8	1,999	34.9	1,721	40.5	1,814	50.5	1,824	48.8	1,840	50.888	49.65	824.39	-34.31

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued)

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
463	2	2	1	1	2	2	2	1	2	29.3	2,356	25.6	2,370	26.8	2,402	21.6	2,158	24.7	2,526	27.7	2,290	23.8	2,189	20.8	2,340	25.038	25.15	1,037.04	-28.02
464	2	2	1	1	2	2	2	2	2	37.4	2,427	49.4	2,489	50.4	2,661	50.2	2,440	48.7	2,533	49.5	2,534	35.2	2,404	52.1	2,561	46.613	49.45	1,127.93	-33.44
465	2	2	1	2	1	1	1	1	2	13.5	1,275	13.7	1,149	16.5	1,433	13.6	1,319	14.1	1,351	14.3	1,493	15.1	1,336	14	1,345	14.350	14.05	613.92	-23.16
466	2	2	1	2	1	1	1	2	2	31.6	1,470	42.6	1,507	37.2	1,544	35.6	1,483	36.7	1,524	28.2	1,405	34.2	1,462	41.2	1,468	35.913	36.15	661.83	-31.17
467	2	2	1	2	1	1	2	1	2	14.1	1,861	13.1	1,866	13.7	1,831	13.7	1,849	14.3	2,094	16.3	2,006	14.2	1,827	13.4	1,894	14.100	13.90	854.86	-23.00
468	2	2	1	2	1	1	2	2	2	28.1	1,960	27.7	2,009	36.3	2,011	20.3	2,003	32.5	2,074	26.3	2,029	30.6	2,042	36.8	2,001	29.825	29.35	922.64	-29.62
469	2	2	1	2	1	2	1	1	2	32.3	1,902	22	1,784	28	1,777	23.4	1,730	29.2	1,852	22.2	1,852	28.8	1,801	25.6	1,863	26.438	26.80	836.10	-28.52
470	2	2	1	2	1	2	1	2	2	47.7	1,880	44	1,871	41.6	2,102	26.2	1,811	42.5	1,923	39.1	1,954	34.8	2,065	40	2,018	39.488	40.80	926.54	-32.03
471	2	2	1	2	1	2	2	1	2	21.7	2,288	20.5	2,226	21.8	2,262	22.6	2,330	22	2,388	26.7	2,398	21.8	2,360	23.1	2,261	22.525	21.90	1,059.45	-27.08
472	2	2	1	2	1	2	2	2	2	31.3	2,481	40.9	2,548	38.8	2,289	42.5	2,448	40.5	2,476	31	2,514	36.7	2,533	31	2,362	36.588	37.75	1,116.56	-31.33
473	2	2	1	2	2	1	1	1	2	14.1	1,412	13.5	1,210	14.1	1,273	14	1,375	13.2	1,327	13.7	1,364	14.3	1,320	14.9	1,458	13.975	14.05	637.68	-22.91
474	2	2	1	2	2	1	1	2	2	53.8	1,500	58.8	1,450	58.9	1,466	62	1,596	33.3	1,416	57	1,513	37.8	1,350	54.7	1,431	52.038	55.85	619.14	-34.48
475	2	2	1	2	2	1	2	1	2	14.1	1,873	14.1	1,941	0	0	14.7	1,873	12.5	1,803	13.2	1,848	11.9	1,652	13.2	1,867	11.713	13.20	811.25	-21.97
476	2	2	1	2	2	1	2	2	2	43.2	2,141	51.5	1,915	41.9	1,921	43.9	2,139	44.6	2,082	30.1	2,041	27.6	1,947	38.2	1,922	40.125	42.55	875.86	-32.21
477	2	2	1	2	2	2	1	1	2	25.2	1,859	23.6	1,924	23.8	1,781	26.9	1,894	24.8	1,753	22.1	1,738	23.7	1,666	21.4	1,632	23.938	23.75	752.10	-27.60
478	2	2	1	2	2	2	1	2	2	51.5	1,954	62.4	2,002	45.2	1,812	54.2	1,964	41.5	1,889	55.2	2,020	50.4	1,889	60.8	2,036	52.650	52.85	885.44	-34.50
479	2	2	1	2	2	2	2	1	2	24.8	2,281	22.3	2,307	24.6	2,460	22.8	2,233	22.1	2,278	29.5	2,453	25.4	2,459	23.2	2,321	24.338	23.90	1,095.71	-27.76
480	2	2	1	2	2	2	2	2	2	51.6	2,517	47.6	2,398	51.7	2,432	42.4	2,396	34.1	2,449	46	2,535	50.7	2,552	51	2,522	46.888	49.15	1,153.35	-33.49
481	2	2	2	1	1	1	1	1	2	13.8	1,242	15.8	1,434	13.6	1,326	15.9	1,465	13.4	1,309	12.3	1,128	14.1	1,319	16.1	1,378	14.375	13.95	617.89	-23.19
482	2	2	2	1	1	1	1	2	2	39.2	1,560	40.3	1,312	25.6	1,364	41.1	1,506	35.4	1,535	36.7	1,349	30.3	1,382	34.3	1,375	35.363	36.05	621.30	-31.06
483	2	2	2	1	1	1	2	1	2	14.3	1,766	12.6	1,798	14	1,915	14.5	1,985	13.8	1,875	12.9	1,918	14.2	1,900	13.4	1,898	13.713	13.90	872.73	-22.75
484	2	2	2	1	1	1	2	2	2	22.9	2,003	24.1	1,948	21.8	1,901	30.5	2,013	27.9	1,958	21.7	1,902	20.9	1,978	29.6	2,155	24.925	23.50	946.30	-28.02

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued)

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
485	2	2	2	1	1	2	1	1	2	30	1,868	29.1	1,823	23.9	1,854	27.1	1,909	29.5	1,876	28.8	1,873	32.7	1,916	27.1	1,786	28.525	28.95	844.57	-29.14
486	2	2	2	1	1	2	1	2	2	45.8	2,117	52	1,982	34.9	1,780	43.1	1,879	41.4	1,930	33.9	1,897	48.2	1,918	55.6	1,957	44.363	44.45	877.60	-33.05
487	2	2	2	1	1	2	2	1	2	27.9	2,312	26.5	2,491	24.5	2,343	30.1	2,526	19.3	2,276	26.2	2,241	24.8	2,317	22.7	2,346	25.250	25.50	1,067.39	-28.11
488	2	2	2	1	1	2	2	2	2	29.6	2,358	36.2	2,478	40	2,577	40	2,539	40.3	2,438	40.5	2,398	30.2	2,462	34.1	2,538	36.363	38.10	1,139.98	-31.27
489	2	2	2	1	2	1	1	1	2	13.1	1,326	15.8	1,465	14.8	1,379	14.4	1,307	13.7	1,367	13.6	1,183	15.7	1,398	15.1	1,386	14.525	14.60	637.79	-23.26
490	2	2	2	1	2	1	1	2	2	49.4	1,509	33.5	1,392	48.3	1,602	48	1,323	51	1,278	57.2	1,446	59.4	1,501	46.7	1,511	49.188	48.85	675.01	-33.93
491	2	2	2	1	2	1	2	1	2	14.1	1,906	14.4	1,787	13.2	1,898	14.3	1,971	14.1	1,903	13.6	1,865	15.4	1,890	12.8	1,868	13.988	14.10	863.37	-22.93
492	2	2	2	1	2	1	2	2	2	51.5	2,080	41	1,970	20.5	1,904	40.5	1,946	47.5	2,105	45.4	2,107	42.6	2,113	48.9	2,071	42.238	44.00	949.51	-32.71
493	2	2	2	1	2	2	1	1	2	24.1	1,787	30.7	2,004	22.4	1,685	29.7	1,740	27.6	1,968	28.7	1,841	26.6	1,720	26.2	1,800	27.000	27.10	802.42	-28.67
494	2	2	2	1	2	2	1	2	2	57.5	2,003	61.7	1,871	56.2	2,139	52.1	1,873	59	1,949	62.6	1,873	59.2	1,991	46.2	1,993	56.813	58.25	895.19	-35.12
495	2	2	2	1	2	2	2	1	2	27.5	2,331	30	2,508	26.7	2,497	25.7	2,289	22.3	2,261	24.1	2,207	25.8	2,302	27.2	2,152	26.163	26.25	1,019.63	-28.38
496	2	2	2	1	2	2	2	2	2	55.5	2,599	53.2	2,506	55.2	2,607	26.3	2,372	58.7	2,597	56.3	2,622	48.3	2,553	46.2	2,429	49.963	54.20	1,130.10	-34.14
497	2	2	2	2	1	1	1	1	2	14.1	1,324	12.5	1,205	13.5	1,340	13.9	1,378	14.2	1,205	14.9	1,304	14.6	1,441	14.9	1,418	14.075	14.15	655.35	-22.98
498	2	2	2	2	1	1	1	2	2	32.3	1,433	32.7	1,589	34.1	1,441	23.2	1,432	32.6	1,551	40.3	1,458	38.4	1,517	32.9	1,419	33.313	32.80	665.02	-30.54
499	2	2	2	2	1	1	2	1	2	14.3	1,977	14.2	1,885	15.5	1,919	13.5	1,808	13.8	1,797	14.3	1,921	14.3	1,731	14.7	1,897	14.325	14.30	834.30	-23.13
500	2	2	2	2	1	1	2	2	2	29.9	1,991	25.2	1,878	25.3	1,978	32.5	2,079	24.8	2,032	32.2	2,022	31.9	2,111	30.4	2,045	29.025	30.15	948.99	-29.31
501	2	2	2	2	1	2	1	1	2	26.6	1,898	33	1,794	27.8	1,845	33.4	1,836	31.3	1,758	27.9	1,795	29	1,827	30.1	1,920	29.888	29.55	853.74	-29.54
502	2	2	2	2	1	2	1	2	2	40.3	1,991	46.6	2,018	39.1	1,936	36.7	1,957	43.7	1,881	43.7	1,939	42.1	2,056	27.8	1,778	40.000	41.20	871.28	-32.12
503	2	2	2	2	1	2	2	1	2	32.3	2,394	29.5	2,352	26.6	2,450	30.6	2,404	30	2,381	35.6	2,405	31.4	2,294	33	2,334	31.125	31.00	1,056.99	-29.89
504	2	2	2	2	1	2	2	2	2	40.5	2,419	36.8	2,364	46.5	2,495	37.6	2,641	47.5	2,495	50.1	2,654	37.2	2,517	40.9	2,476	42.138	40.70	1,135.74	-32.55
505	2	2	2	2	2	1	1	1	2	14.3	1,334	13.2	1,338	14.5	1,289	12.2	1,321	15.5	1,460	12.7	1,338	13.9	1,361	13.4	1,224	13.713	13.65	593.09	-22.76
506	2	2	2	2	2	1	1	2	2	61.5	1,496	38.2	1,524	57.5	1,405	52.9	1,545	34.8	1,398	56.4	1,466	53.1	1,541	46.9	1,462	50.163	53.00	672.21	-34.14

Appendix C1. Full factorial data set featuring delay (Traffic flow case study)...(continued)

										R1		R2		R3		R4		R5		R6		R7		R8					
Run	VM	SD	PS1	PS2	PS3	PM1	PM2	PM3	CP	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	**Mean**	**Median**	**STD**	**SNR**
507	2	2	2	2	2	1	2	1	2	14.7	1,889	14.9	1,959	15	1,925	16.3	1,877	15	1,865	14.3	1,921	12.5	1,807	14	1,942	14.588	14.80	861.52	-23.30
508	2	2	2	2	2	1	2	2	2	39.1	1,846	46.9	2,029	43.6	2,040	37.7	2,060	41.8	1,910	48	2,080	46.8	2,140	37.7	1,918	42.700	42.70	921.33	-32.65
509	2	2	2	2	2	2	1	1	2	28.1	1,831	27.5	1,742	32.5	1,741	33.9	1,829	29.4	1,865	36	1,925	30.6	1,836	28	1,825	30.750	30.00	832.91	-29.80
510	2	2	2	2	2	2	1	2	2	50	1,894	55.5	1,974	34.1	1,952	54.5	1,836	61.7	1,990	58.5	2,057	42.8	1,853	55.3	2,000	51.550	54.90	868.48	-34.36
511	2	2	2	2	2	2	2	1	2	27.6	2,304	26.7	2,276	31.4	2,252	32.3	2,348	29.2	2,411	30.7	2,264	30.2	2,497	30.4	2,359	29.813	30.30	1,110.83	-29.50
512	2	2	2	2	2	2	2	2	2	53.2	2,438	54.8	2,543	48.3	2,476	39.9	2,386	51.8	2,483	52.6	2,591	50	2,346	50.3	2,626	50.113	51.05	1,130.09	-34.03

Appendix C1. Full factorial data set featuring delay (Traffic flow case study).

APPENDIX C2
TAGUCHI L_{32} DATA SET
FEATURING *DELAY*
(TRAFFIC FLOW CASE STUDY)

Abbreviations

Run – run number.
FF Equiv. – Equivalent run in the full factorial array (Appendix C1).

Factors:
VM - Vehicle Mix (%HGV).
SD – Speed Distribution (km/hr).
PS1 – Profile 1 Slope.
PS2 – Profile 2 Slope.
PS3 – Profile 3 Slope.
PM1 - Profile 1 Magnitude.
PM2 - Profile 2 Magnitude.
PM3 - Profile 3 Magnitude.
CP – Controller Type.
ER1 – Error term 1.
ER2 – Error term 2.

Repetitions:
R1 – Repetition One.
R2 – Repetition Two.
R3 – Repetition Three.
R4 – Repetition Four.
R5 – Repetition Five.
R6 – Repetition Six.
R7 – Repetition Seven.
R8 – Repetition Eight.
Delay – Delay
Vehs – Number of vehicles corresponding to Delay

Responses (Stats calculated for each run only):
Mean – Mean.
Median - Median
STD – Standard Deviation.
SNR – Signal-to-Noise Ratio.

Notes:
- **A*B** represents the interaction between factors **A** and **B**.
- Error terms **ER1** and **ER2** are in practice the same. In fact, they can be substituted by a more general term, eg **ERR,** if desired. However, they have been differentiated in order to allow (interaction) aliasing identification if required by further studies.
- Linear graph as Taguchi's original notation (from Peace, 1993).

Run	FF equiv.	VM	SD	VM*SD	PS1	VM*PS1	SD*PS1	PS2*PS3	PS2	VM*PS2	SD*PS2	PS1*PS3	PS1*PS2	SD*PS3	VM*PS3	PS3	PM1	VM*PM1	SD*PM1	PM2	PS1*PM1	PM3	CP	VM*CP	PS2*PM1	ER1	ER2	SD*ER1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	264	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2
3	25	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	2	2	2	2
4	288	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1
5	298	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1
6	47	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	2	2	2	2
7	306	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
8	55	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	1	1	1	1
9	331	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2
10	78	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	2	2	1	1
11	339	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2	2	2	1	1
12	86	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	1	1	2	2
13	100	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2
14	357	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	2	2	1	1
15	124	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1
16	381	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	1	1	2	2
17	140	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
18	397	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	2	1	2	1
19	148	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2	2	1	2	1
20	405	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	1	2	1	2

Appendix B2. Taguchi data set featuring delay (Traffic flow case study), using Linear Graph II.

						R1		R2		R3		R4		R5		R6		R7		R8					
Run	FF Equiv.	PS3*PM2	PS2*PM3	PS1*ER2	PS3*PM1	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Mean	Median	STD	STB
1	1	1	1	1	1	13	1,292	13	1,370	13	1,270	13	1,435	13	1,187	14	1,268	13	1,279	13	1,320	13.125	13	595.558	-22.365
2	264	2	2	2	2	19	2,391	23.5	2,565	26.9	2,691	15.9	2,381	23.5	2,550	22.8	2,445	20	2,535	21.8	2,461	21.675	22.3	1146.371	-26.809
3	25	2	2	2	2	13	1,248	12	1,232	13	1,232	13	1,282	13	1,337	12	1,295	13	1,391	13	1,260	12.75	13	608.732	-22.115
4	288	1	1	1	1	18.7	2,516	23.8	2,629	19	2,462	20.3	2,458	18.5	2,374	30.4	2,688	36.4	2,584	23	2,581	23.7625	21.65	1185.388	-27.790
5	298	2	2	2	2	17.5	1,410	54.1	1,517	25.4	1,665	46	1,494	37.5	1,560	35.2	1,495	28	1,635	24.2	1,363	33.4875	31.6	681.244	-30.973
6	47	1	1	1	1	13	2,412	14	2,477	13	2,436	13	2,292	14	2,202	14	2,266	14	2,335	14	2,406	13.625	14	1091.244	-22.692
7	306	1	1	1	1	16.9	1,314	19.5	1,381	23.8	1,462	16.8	1,460	20.3	1,351	18.7	1,559	18.1	1,453	18.1	1,482	19.025	18.4	670.419	-25.640
8	55	2	2	2	2	13	2,478	14	2,378	13	2,483	13	2,432	14	2,158	13	2,379	13	2,394	13	2,277	13.25	13	1075.409	-22.449
9	331	1	1	2	2	12	1,830	11.7	1,868	12.3	1,943	11.8	1,838	12.7	1,907	12.3	1,956	11.7	1,814	12.9	1,824	12.175	12.15	836.421	-21.715
10	78	2	2	1	1	15	2,208	16	2,021	16	2,038	15	1,865	16	1,957	16	2,067	15	1,939	16	2,107	15.625	16.00	930.299	-23.881
11	339	2	2	1	1	11.8	1,890	11.7	1,777	11.7	1,886	12	1,932	12	1,797	11.4	1,727	12	1,816	11.2	1,767	11.725	11.75	823.961	-21.385
12	86	1	1	2	2	16	1,937	16	2,078	15	2,080	15	2,048	17	2,195	16	1,974	16	1,990	16	1,957	15.875	16	906.267	-24.020
13	100	2	2	1	1	12	1,972	12	2,051	12	2,025	13	2,246	12	2,075	12	2,095	12	2,023	12	2,006	12.125	12	926.911	-21.677
14	357	1	1	2	2	19.1	1,817	16.3	1,791	22.6	1,794	16.8	1,847	14.7	1,724	22.5	1,859	17	1,887	18.6	1,806	18.45	17.8	846.404	-25.411
15	124	1	1	2	2	12	2,018	13	2,043	13	1,924	13	2,054	12	2,106	13	2,082	13	2,009	13	2,098	12.75	13	945.022	-22.115
16	381	2	2	1	1	15	1,808	20.1	1,872	17.8	1,852	17.5	1,758	21.7	1,805	19.5	1,880	17.4	1,819	21.5	1,837	18.8125	18.65	837.606	-25.545
17	140	1	2	1	2	14	2,024	14	1,878	15	2,106	13	1,970	13	1,944	14	2,083	16	2,059	14	2,165	14.125	14	971.676	-23.018
18	397	2	1	2	1	28.6	1,725	30.8	1,904	23.7	1,602	30.2	1,934	27.7	1,853	29.4	1,814	25.9	1,642	30.9	1,994	28.4	29	833.751	-29.097
19	148	2	1	2	1	16	1,990	14	1,924	14	1,911	16	2,100	15	2,089	13	2,074	16	2,192	14	1,922	14.75	14.5	948.167	-23.399
20	405	1	2	1	2	24.8	1,761	21.1	1,679	23	1,788	23	1,748	22.5	1,781	19.9	1,784	20.7	1,683	21.7	1,865	22.0875	22.1	812.300	-26.902

Appendix B2. Taguchi data set featuring delay (Traffic flow case study), using Linear Graph II.

Run	FF equiv.	VM	SD	VM*SD	PS1	VM*PS1	SD*PS1	PS2*PS3	PS2	VM*PS2	SD*PS2	PS1*PS3	PS1*PS2	SD*PS3	VM*PS3	PS3	PM1	VM*PM1	SD*PM1	PM2	PS1*PM1	PM3	CP	VM*CP	PS2*PM1	ER1	ER2	SD*ER1
21	419	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2
22	166	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	2	1	2	1
23	443	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1
24	190	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	1	2	1	2
25	450	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1
26	199	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	2	1	1	2
27	474	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2
28	223	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	1	2	2	1
29	233	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1
30	496	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	2	1	1	2
31	241	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2
32	504	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	1	2	2	1

Appendix B2. Taguchi data set featuring delay (Traffic flow case study), using Linear Graph II.

						R1		R2		R3		R4		R5		R6		R7		R8					
Run	FF Equiv.	PS3*PM2	PS2*PM3	PS1*ER2	PS3*PM1	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Delay	Vehs	Mean	Median	STD	STB
21	419	2	1	2	1	13.5	1,937	13.4	1,851	15.9	2,021	13.3	1,877	13.2	1,944	13.4	1,930	12.6	1,722	12.8	1,946	13.5125	13.35	844.721	-22.636
22	166	1	2	1	2	19	1,998	21	1,879	17	1,901	19	1,864	19	1,984	21	2,063	20	2,010	18	2,024	19.25	19	924.748	-25.708
23	443	1	2	1	2	14.5	1,808	13.2	1,844	12.8	1,983	13.4	1,894	14.2	1,844	13	1,924	14.7	1,868	14.8	1,844	13.825	13.8	852.928	-22.826
24	190	2	1	2	1	22	1,963	19	1,873	20	1,966	19	1,920	21	2,073	18	1,874	20	2,199	21	2,092	20	20	984.409	-26.037
25	450	1	2	2	1	46.9	1,553	23.6	1,422	25.8	1,455	39.9	1,444	44.1	1,481	29.8	1,490	43	1,513	42.3	1,482	36.925	41.1	677.101	-31.571
26	199	2	1	1	2	16	2,362	15	2,332	17	2,291	15	2,570	14	2,405	13	2,241	14	2,385	16	2,241	15	15	1064.464	-23.551
27	474	2	1	1	2	53.8	1,500	58.8	1,450	58.9	1,466	62	1,596	33.3	1,416	57	1,513	37.8	1,350	54.7	1,431	52.0375	55.85	619.137	-34.480
28	223	1	2	2	1	16	2,486	16	2,341	15	2,451	16	2,389	15	2,336	16	2,393	15	2,280	15	2,410	15.5	15.5	1078.832	-23.811
29	233	2	1	1	2	14	1,344	15	1,251	14	1,330	14	1,475	15	1,430	14	1,311	14	1,332	14	1,424	14.25	14	631.734	-23.080
30	496	1	2	2	1	55.5	2,599	53.2	2,506	55.2	2,607	26.3	2,372	58.7	2,597	56.3	2,622	48.3	2,553	46.2	2,429	49.9625	54.2	1130.095	-34.135
31	241	1	2	2	1	14	1,256	14	1,326	14	1,341	14	1,327	14	1,469	13	1,419	14	1,299	13	1,399	13.75	14	618.640	-22.770
32	504	2	1	1	2	40.5	2,419	36.8	2,364	46.5	2,495	37.6	2,641	47.5	2,495	50.1	2,654	37.2	2,517	40.9	2,476	42.1375	40.7	1135.735	-32.551

Appendix B2. Taguchi data set featuring delay (Traffic flow case study), using Linear Graph II.

APPENDIX D1
FULL FACTORIAL DATA SETS
FEATURING *FITNESS*
(GA OPTIMISATION CASE STUDY)

Abbreviations

Run – run number.

Factors:
POPSIZE - Population Size
MAXGEN – Number of generations.
XOVER – Crossover probability.
MUTPRO – Mutation probability.
TOURN – Tournament size/winners.

Replications:
Seeds – Seeds required for random number generation. Each value (0.0251, 0.152, 0.253, 0.4174, 0.54, 0.756, 0.8757, 0.958) represents a replication

Responses (Stats calculated for each run only):
Mean – Mean.
STD – Standard Deviation.
SNR – Signal-to-Noise Ratio.
Peak Value – maximum value amongst the eight replications of each run.

						Seeds											
Run	**POPSIZE**	**MAXGEN**	**XOVER**	**TOURN**	**MUTPRO**	**0.0251**	**0.152**	**0.253**	**0.4174**	**0.54**	**0.756**	**0.8757**	**0.958**	**Mean**	**STD**	**SNR**	**Peak**
1	100	99	0.25	1	0.001	6058.8	5633.1	2214.35	15177.3	526.3	5195.5	3219.8	7214.2	5654.92	4432.86	62.98	15177.3
2	1000	25	0.25	1	0.001	51192.3	8537	2741.63	7707.6	1590.36	6705.7	18708.6	48151	18166.77	20128.97	71.36	51192.3
3	1000	25	0.25	2	0.001	7277.5	8081.3	4501.38	25681.4	1590.36	8934.6	6966.4	10175.1	9151.01	7196.81	71.84	25681.4
4	1000	25	0.25	1	0.01	24649.9	11731.5	2741.63	8344.8	1590.36	18750.9	15581	10141.7	11691.47	7825.06	71.48	24649.9
5	1000	99	0.9	1	0.001	36740.8	50262.5	2788.22	51962.5	1590.36	7686.7	50740.7	71657.5	34178.66	26751.94	71.68	71657.5
6	100	25	0.25	1	0.01	6058.8	3926	2214.35	2843.7	526.3	5195.5	3219.8	7214.2	3899.83	2175.35	62.82	7214.2
7	100	25	0.25	2	0.001	6058.8	3926	2214.35	1062.1	526.3	5195.5	3219.8	7214.2	3677.13	2380.44	62.09	7214.2
8	100	25	0.9	1	0.01	2227.7	2595.9	2214.35	10162.1	442.95	3554.6	3219.8	4126.7	3568.01	2884.82	61.33	10162.1
9	1000	99	0.9	1	0.01	26609.1	7211.3	2788.22	18460.5	1590.36	37904.3	26296.5	15203	17007.91	12852.80	71.60	37904.3
10	100	99	0.25	1	0.01	8983.9	29236.7	2214.35	7221.9	526.3	5195.5	6126.4	7214.2	8339.91	8887.95	63.09	29236.7
11	100	25	0.9	1	0.001	5602.6	2595.4	2214.35	50582.3	442.95	2246.3	4311	3472.1	8933.38	16899.02	61.38	50582.3
12	1000	25	0.9	2	0.001	6314.2	18370.9	3554.24	5459.8	1590.36	18357.9	15602.5	5783	9379.11	6891.84	71.45	18370.9
13	100	99	0.9	1	0.001	8209.5	4926.1	2214.35	51962.5	442.95	24109.5	24138.5	7212.3	15401.96	17382.47	61.72	51962.5
14	100	99	0.25	2	0.001	6086.4	2927.1	2214.35	15336	526.3	4946.9	5901.7	3407	5168.22	4523.13	62.88	15336
15	100	25	0.25	1	0.001	6058.8	3947.1	2214.35	1981.9	526.3	3915.1	24372	24526.3	8442.73	10014.43	62.77	24526.3
16	1000	25	0.9	1	0.001	36740.8	11654.3	2788.22	18620.7	1590.36	4901.3	20857.8	11606.8	13595.04	11698.18	71.35	36740.8
17	100	25	0.9	2	0.001	9002.8	10920	2214.35	5805.4	526.3	2246.3	1639.3	1577.5	4241.49	3881.81	62.19	10920
18	1000	99	0.25	2	0.01	51192.3	18950.7	4501.38	50615.2	1590.36	26242.6	18518.3	11370.2	22872.63	19049.17	72.40	51192.3
19	100	99	0.25	2	0.01	7634.5	4603	2214.35	14921.3	526.3	2826.5	13386.2	4024.4	6267.07	5297.77	62.93	14921.3
20	1000	99	0.25	2	0.001	51204.1	11414.1	4501.38	25681.4	1590.36	49086.1	37172.4	24526.3	25647.02	19142.64	72.43	51204.1
21	100	99	0.9	2	0.001	9002.8	10920	2214.35	50582.3	526.3	4093.4	72987.9	5639.1	19495.77	26989.83	63.09	72987.9
22	100	99	0.9	2	0.01	6058.8	10920	2214.35	3022.3	526.3	6534.3	4891.8	5436	4950.48	3171.05	62.95	10920
23	100	99	0.9	1	0.01	6675.2	29494.1	2214.35	15260.8	442.95	3554.6	4165.6	4126.7	8241.79	9681.00	61.61	29494.1
24	100	25	0.9	2	0.01	5602.6	4707.4	2214.35	2473.3	526.3	2246.3	4000.8	4767.9	3317.37	1715.14	62.64	5602.6
25	1000	25	0.9	1	0.01	13534.3	5424.3	2788.22	8296.5	1590.36	10178.7	6604.1	8482.2	7112.34	3895.44	71.08	13534.3
26	1000	99	0.25	1	0.001	51192.3	49019.7	2788.22	74317.5	1590.36	15474.2	18708.6	48809.4	32737.54	26605.12	71.77	74317.5
27	1000	99	0.9	2	0.01	24985.5	11733.2	3554.24	19119	1590.36	12678	26270.6	35917.9	16981.10	11812.53	72.09	35917.9
28	1000	25	0.9	2	0.01	6613.8	5204.4	3554.24	7242.6	1590.36	8568.3	26270.6	4692.5	7967.10	7711.10	71.15	26270.6
29	100	25	0.25	2	0.01	1945.9	3256.6	2214.35	14921.3	526.3	2709.8	4165.6	3493.3	4154.14	4489.04	62.54	14921.3
30	1000	99	0.9	2	0.001	15273.9	50010.4	3554.24	18460.5	1590.36	51753.8	15602.5	50285.4	25816.39	21410.65	72.16	51753.8
31	1000	99	0.25	1	0.01	24826.5	11731.5	2788.22	51962.5	1590.36	18750.9	15581	36547	20472.25	17077.69	71.70	51962.5
32	1000	25	0.25	2	0.01	50312.5	18950.7	4501.38	50615.2	1590.36	11450.5	11270.4	7980.9	19583.99	19743.84	72.22	50615.2

Appendix D1 – Table 1 Full factorial data set featuring fitness (RotChr off) (GA optimisation case study).

						Seeds											
Run	**POPSIZE**	**MAXGEN**	**XOVER**	**TOURN**	**MUTPRO**	**0.0251**	**0.152**	**0.253**	**0.4174**	**0.54**	**0.756**	**0.8757**	**0.958**	**Mean**	**STD**	**SNR**	**Peak**
1	100	99	0.25	1	0.001	4426.22	5428.44	725.08	5561.80	526.06	1536.53	6005.60	4151.54	3545.16	2265.07	61.15	6005.60
2	1000	25	0.25	1	0.001	11872.50	6603.32	5915.91	14884.99	1593.36	3323.04	6005.60	38131.91	11041.33	11768.75	71.43	38131.91
3	1000	25	0.25	2	0.001	11470.67	11256.86	5915.91	24432.02	1593.36	3192.32	6005.60	10077.15	9242.99	7142.41	71.43	24432.02
4	1000	25	0.25	1	0.01	11872.50	29085.49	5915.91	12585.62	1593.36	3323.04	6005.60	18601.34	11122.86	9151.37	71.56	29085.49
5	1000	99	0.9	1	0.001	26447.95	8729.86	5202.03	42256.77	1593.36	2620.91	15532.98	19199.69	15197.94	13938.07	71.26	42256.77
6	100	25	0.25	1	0.01	5486.09	5428.44	725.08	1800.11	526.06	1536.53	6005.60	3737.54	3155.68	2278.43	60.96	6005.60
7	100	25	0.25	2	0.001	1716.69	3302.69	1846.50	6330.83	526.06	1536.53	3114.64	6526.17	3112.52	2228.75	62.12	6526.17
8	100	25	0.9	1	0.01	2967.65	2948.85	1365.68	4894.74	443.01	1536.53	6005.60	2560.52	2840.32	1850.38	60.90	6005.60
9	1000	99	0.9	1	0.01	52438.61	12783.84	5202.03	13596.76	1593.36	2620.91	15532.98	38131.91	17737.55	18177.40	71.30	52438.61
10	100	99	0.25	1	0.01	5486.09	11920.38	725.08	7218.03	526.06	1536.53	6005.60	3737.54	4644.41	3871.65	61.18	11920.38
11	100	25	0.9	1	0.001	2471.96	3302.69	1365.68	6335.88	443.01	1536.53	6005.60	25740.48	5900.23	8295.63	60.99	25740.48
12	1000	25	0.9	2	0.001	8910.79	8910.79	8910.79	8910.79	8910.79	8910.79	8910.79	8910.79	8910.79	0.00	79.00	8910.79
13	100	99	0.9	1	0.001	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48
14	100	99	0.25	2	0.001	6526.17	6526.17	6526.17	6526.17	6526.17	6526.17	6526.17	6526.17	6526.17	0.00	76.29	6526.17
15	100	25	0.25	1	0.001	3737.54	3737.54	3737.54	3737.54	3737.54	3737.54	3737.54	3737.54	3737.54	0.00	71.45	3737.54
16	1000	25	0.9	1	0.001	19199.69	19199.69	19199.69	19199.69	19199.69	19199.69	19199.69	19199.69	19199.69	0.00	85.67	19199.69
17	100	25	0.9	2	0.001	12723.90	12723.90	12723.90	12723.90	12723.90	12723.90	12723.90	12723.90	12723.90	0.00	82.09	12723.90
18	1000	99	0.25	2	0.01	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48
19	100	99	0.25	2	0.01	6558.95	6558.95	6558.95	6558.95	6558.95	6558.95	6558.95	6558.95	6558.95	0.00	76.34	6558.95
20	1000	99	0.25	2	0.001	50440.34	50440.34	50440.34	50440.34	50440.34	50440.34	50440.34	50440.34	50440.34	0.00	94.06	50440.34
21	100	99	0.9	2	0.001	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48
22	100	99	0.9	2	0.01	52587.65	52587.65	52587.65	52587.65	52587.65	52587.65	52587.65	52587.65	52587.65	0.00	94.42	52587.65
23	100	99	0.9	1	0.01	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48
24	100	25	0.9	2	0.01	2471.81	2471.81	2471.81	2471.81	2471.81	2471.81	2471.81	2471.81	2471.81	0.00	67.86	2471.81
25	1000	25	0.9	1	0.01	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	0.00	91.63	38131.91
26	1000	99	0.25	1	0.001	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	0.00	91.63	38131.91
27	1000	99	0.9	2	0.01	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48
28	1000	25	0.9	2	0.01	4116.91	4116.91	4116.91	4116.91	4116.91	4116.91	4116.91	4116.91	4116.91	0.00	72.29	4116.91
29	100	25	0.25	2	0.01	3404.51	3404.51	3404.51	3404.51	3404.51	3404.51	3404.51	3404.51	3404.51	0.00	70.64	3404.51
30	1000	99	0.9	2	0.001	75389.57	75389.57	75389.57	75389.57	75389.57	75389.57	75389.57	75389.57	75389.57	0.00	97.55	75389.57
31	1000	99	0.25	1	0.01	18601.34	18601.34	18601.34	18601.34	18601.34	18601.34	18601.34	18601.34	18601.34	0.00	85.39	18601.34
32	1000	25	0.25	2	0.01	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48

Appendix D1 – Table 2 Full factorial data set featuring fitness (RotChr on – Gene 1 locked in first location) (GA optimisation case study).

						Seeds											
Run	POPSIZE	MAXGEN	XOVER	TOURN	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	Mean	STD	SNR	Peak
1	100	99	0.25	1	0.001	5630.67	2767.66	2593.76	4029.12	286.88	1128.91	6101.74	4711.29	3406.25	2080.16	57.77	6101.74
2	1000	25	0.25	1	0.001	69193.01	6604.98	6596.60	6617.37	1728.50	7575.21	24577.83	7764.70	16332.27	22390.65	72.60	69193.01
3	1000	25	0.25	2	0.001	49058.75	6687.03	6460.18	8971.05	2706.40	2597.14	6073.28	7764.70	11289.82	15423.81	73.15	49058.75
4	1000	25	0.25	1	0.01	74560.82	8570.08	6596.60	19113.21	2706.40	7575.21	24577.83	11761.87	19432.75	23383.93	75.97	74560.82
5	1000	99	0.9	1	0.001	14626.27	13626.61	6460.18	50031.57	2706.40	2600.57	18306.91	51225.59	19948.01	19764.36	73.95	51225.59
6	100	25	0.25	1	0.01	4414.03	3913.23	2097.13	3327.12	2706.40	1535.89	3323.57	26019.46	5917.10	8175.83	68.67	26019.46
7	100	25	0.25	2	0.001	2531.06	8937.79	1394.69	2538.45	2706.40	1535.89	6026.85	2964.00	3579.39	2590.50	67.16	8937.79
8	100	25	0.9	1	0.01	6051.17	2596.50	1714.45	2426.59	751.90	1649.06	6342.21	2964.00	3061.98	2051.96	64.32	6342.21
9	1000	99	0.9	1	0.01	13423.32	50031.57	6460.18	18579.58	2706.40	2600.57	18306.91	50997.85	20388.30	19620.79	73.97	50997.85
10	100	99	0.25	1	0.01	6051.17	4776.67	6418.16	49319.54	2706.40	1535.89	5888.72	26019.46	12839.50	16628.69	70.66	49319.54
11	100	25	0.9	1	0.001	2409.55	7257.06	1714.45	2932.69	751.90	1649.06	6342.21	2964.00	3252.62	2319.74	64.37	7257.06
12	1000	25	0.9	2	0.001	4131.67	7240.57	9393.40	37079.19	1728.50	4628.36	4284.74	4940.42	9178.36	11500.54	71.50	37079.19
13	100	99	0.9	1	0.001	3942.52	6664.65	1254.94	15353.98	286.88	1104.78	2780.41	24605.88	6999.25	8617.65	57.62	24605.88
14	100	99	0.25	2	0.001	4785.11	18284.45	2593.76	2946.38	286.88	923.44	8902.29	8857.21	5947.44	5955.63	57.68	18284.45
15	100	25	0.25	1	0.001	3119.67	2593.91	2097.13	4029.12	286.88	1128.91	2798.50	2953.06	2375.90	1185.76	57.66	4029.12
16	1000	25	0.9	1	0.001	18317.30	13533.42	9393.40	11747.84	2139.03	6771.66	25793.79	49909.80	17200.78	15046.26	74.73	49909.80
17	100	25	0.9	2	0.001	2883.72	1323.40	1254.94	3560.52	286.88	923.44	2373.21	6004.02	2326.27	1837.81	57.29	6004.02
18	1000	99	0.25	2	0.01	40321.49	40080.72	9393.40	51421.36	1728.50	6771.66	9470.42	49909.80	26137.17	21142.33	73.22	51421.36
19	100	99	0.25	2	0.01	3559.70	29878.40	2593.76	51962.54	286.88	923.44	8902.29	26107.41	15526.80	18690.54	57.71	51962.54
20	1000	99	0.25	2	0.001	51862.38	50743.42	9393.40	51962.54	1728.50	6771.66	9470.42	49324.57	28907.11	23722.86	73.23	51962.54
21	100	99	0.9	2	0.001	2883.72	3650.68	1254.94	4878.54	286.88	4947.60	5025.23	6197.59	3640.65	2042.68	57.85	6197.59
22	100	99	0.9	2	0.01	6384.41	5014.05	1254.94	15313.39	286.88	4947.60	5025.23	18929.21	7144.46	6565.69	57.91	18929.21
23	100	99	0.9	1	0.01	9523.31	6539.47	1254.94	15353.98	286.88	1104.78	2780.41	5659.30	5312.88	5155.09	57.63	15353.98
24	100	25	0.9	2	0.01	2345.38	4125.48	1254.94	3736.95	286.88	923.44	2373.21	18929.21	4246.94	6078.66	57.43	18929.21
25	1000	25	0.9	1	0.01	11726.67	8983.17	9393.40	9821.00	2139.03	6771.66	25793.79	7755.46	10298.02	6870.26	74.26	25793.79
26	1000	99	0.25	1	0.001	37363.32	73437.81	9393.40	74317.50	1728.50	6771.66	15396.41	49909.80	33539.80	29708.08	73.31	74317.50
27	1000	99	0.9	2	0.01	24297.08	50114.77	9393.40	18587.01	1728.50	4628.36	15551.88	51962.54	22032.94	19340.27	72.99	51962.54
28	1000	25	0.9	2	0.01	4425.27	6982.58	9393.40	7228.50	1728.50	4628.36	4284.74	9843.74	6064.39	2784.65	71.64	9843.74
29	100	25	0.25	2	0.01	3559.70	7332.24	2593.76	2637.17	286.88	923.44	8902.29	5495.98	3966.43	3038.95	57.64	8902.29
30	1000	99	0.9	2	0.001	26107.41	26001.79	9393.40	37079.19	1728.50	4628.36	15551.88	13412.22	16737.84	12104.94	72.94	37079.19
31	1000	99	0.25	1	0.01	18360.59	71106.00	9393.40	26214.81	1728.50	6771.66	15396.41	49909.80	24860.15	23908.43	73.27	71106.00
32	1000	25	0.25	2	0.01	5807.19	40080.72	9393.40	9647.96	1728.50	6771.66	5020.27	49909.80	16044.94	18232.71	72.51	49909.80

Appendix D1 – Table 3 Full factorial data set featuring fitness (RotChr on – Gene 2 locked in first location) (GA optimisation case study).

Run	POPSIZE	MAXGEN	XOVER	TOURN	MUTPRO	Seeds 0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	Mean	STD	SNR	Peak
1	100	99	0.25	1	0.001	5443.32	4760.94	2214.09	11860.80	581.29	1068.84	5207.09	4405.81	4442.77	3545.15	62.79	11860.80
2	1000	25	0.25	1	0.001	6672.33	7980.40	30102.66	8032.00	1593.38	6400.06	6894.20	5492.76	9145.97	8708.77	71.81	30102.66
3	1000	25	0.25	2	0.001	6999.38	8486.85	30102.66	4830.11	1593.38	2602.12	3747.97	24414.96	10347.18	10779.96	70.63	30102.66
4	1000	25	0.25	1	0.01	10833.13	15314.64	30102.66	37354.16	1593.38	6400.06	6894.20	49441.07	19741.66	17200.42	72.46	49441.07
5	1000	99	0.9	1	0.001	13434.96	8976.70	30102.66	52354.09	1593.38	6400.06	13434.96	76173.19	25308.75	26214.20	72.56	76173.19
6	100	25	0.25	1	0.01	6702.64	7163.47	2214.09	2457.05	581.29	1068.84	5207.09	1873.81	3408.54	2572.95	62.43	7163.47
7	100	25	0.25	2	0.001	2698.75	1180.36	2214.09	2843.31	263.75	1393.78	4812.32	2949.26	2294.45	1384.39	56.93	4812.32
8	100	25	0.9	1	0.01	2126.95	2206.69	2214.09	2158.16	581.29	622.39	6049.05	3835.54	2474.27	1773.00	60.91	6049.05
9	1000	99	0.9	1	0.01	13574.19	18962.10	30102.66	18827.70	1593.38	6400.06	13434.96	49441.07	19042.02	14986.20	72.63	49441.07
10	100	99	0.25	1	0.01	6702.64	7163.47	2214.09	5083.72	581.29	1068.84	5207.09	2961.97	3872.89	2517.38	62.73	7163.47
11	100	25	0.9	1	0.001	6702.64	3948.83	2214.09	3479.43	581.29	622.39	6049.05	5605.06	3650.35	2380.28	61.27	6702.64
12	1000	25	0.9	2	0.001	4158.38	16395.06	4536.26	5572.39	1593.38	6400.06	6560.33	6902.97	6514.85	4348.42	71.21	16395.06
13	100	99	0.9	1	0.001	10833.13	7257.06	2214.09	6325.56	581.29	622.39	12740.67	5605.06	5772.41	4517.23	61.37	12740.67
14	100	99	0.25	2	0.001	3932.61	5621.76	2214.09	3858.14	263.75	1393.78	4812.32	2949.26	3130.71	1785.45	57.15	5621.76
15	100	25	0.25	1	0.001	1536.76	3903.23	2214.09	11860.80	581.29	1068.84	5207.09	3949.23	3790.17	3634.07	62.37	11860.80
16	1000	25	0.9	1	0.001	7237.97	8496.74	30102.66	9705.70	1593.38	6400.06	6560.33	12548.68	10330.69	8578.84	72.11	30102.66
17	100	25	0.9	2	0.001	8458.78	1866.51	2214.09	6354.73	329.69	1393.78	6049.05	2379.10	3630.72	2907.26	58.84	8458.78
18	1000	99	0.25	2	0.01	71508.15	51345.75	30102.66	11831.36	1593.38	4830.11	49910.77	49441.07	33820.41	25653.65	72.53	71508.15
19	100	99	0.25	2	0.01	3305.19	3643.18	2214.09	5904.46	263.75	1393.78	4812.32	3665.56	3150.29	1819.50	57.15	5904.46
20	1000	99	0.25	2	0.001	18522.89	24498.12	30102.66	10795.17	1593.38	4830.11	49910.77	49486.93	23717.50	18638.33	72.48	49910.77
21	100	99	0.9	2	0.001	8458.78	11347.18	2214.09	6354.73	329.69	1393.78	6346.04	4405.81	5106.26	3755.71	59.01	11347.18
22	100	99	0.9	2	0.01	5870.17	7163.47	2214.09	7179.43	329.69	1393.78	6346.04	8966.85	4932.94	3168.54	59.02	8966.85
23	100	99	0.9	1	0.01	3560.92	6669.61	2214.09	52354.09	581.29	622.39	12740.67	7635.84	10797.36	17286.28	61.34	52354.09
24	100	25	0.9	2	0.01	3555.44	7163.47	2214.09	4174.63	329.69	1393.78	6049.05	1556.72	3304.61	2390.11	58.81	7163.47
25	1000	25	0.9	1	0.01	13574.19	8678.70	30102.66	7185.13	1593.38	6400.06	6560.33	8728.36	10352.85	8640.80	72.10	30102.66
26	1000	99	0.25	1	0.001	71533.48	24307.29	30102.66	10162.15	1593.38	6400.06	50696.32	24569.48	27420.60	23662.76	72.67	71533.48
27	1000	99	0.9	2	0.01	24928.71	37354.05	4536.26	11112.07	1593.38	6400.06	50223.41	50223.41	23296.42	20379.67	72.24	50223.41
28	1000	25	0.9	2	0.01	6672.33	6702.04	4536.26	7670.81	1593.38	6400.06	6560.33	5252.83	5673.50	1907.76	71.34	7670.81
29	100	25	0.25	2	0.01	2832.04	1842.05	2214.09	5904.46	263.75	1393.78	4812.32	2754.61	2752.14	1826.11	57.07	5904.46
30	1000	99	0.9	2	0.001	52238.25	18105.27	4536.26	25838.18	1593.38	6400.06	50223.41	15169.68	21763.06	19827.06	72.25	52238.25
31	1000	99	0.25	1	0.01	11001.97	51345.75	30102.66	37354.16	1593.38	6400.06	50696.32	49441.07	29741.92	20840.60	72.70	51345.75
32	1000	25	0.25	2	0.01	3074.30	3163.88	30102.66	11831.36	1593.38	2602.12	3747.97	5898.76	7751.80	9584.52	69.71	30102.66

Appendix D1 – Table 4 Full factorial data set featuring fitness (RotChr on – Gene 3 locked in first location) (GA optimisation case study).

						Seeds											
Run	**POPSIZE**	**MAXGEN**	**XOVER**	**TOURN**	**MUTPRO**	**0.0251**	**0.152**	**0.253**	**0.4174**	**0.54**	**0.756**	**0.8757**	**0.958**	**Mean**	**STD**	**SNR**	**Peak**
1	100	99	0.25	1	0.001	7763.86	18684.14	1036.44	21000.40	421.21	1536.04	6035.30	7632.50	8013.74	7882.37	60.54	21000.40
2	1000	25	0.25	1	0.001	18289.68	15431.54	3746.40	12633.41	1593.45	2855.52	14806.91	6669.29	9503.27	6526.89	71.05	18289.68
3	1000	25	0.25	2	0.001	12672.70	50244.71	3746.40	7223.81	1593.45	2311.96	6386.34	7718.45	11487.23	16053.21	70.46	50244.71
4	1000	25	0.25	1	0.01	10162.50	15039.32	3746.40	5869.85	1593.45	2855.52	14806.91	7688.30	7720.28	5212.26	70.89	15039.32
5	1000	99	0.9	1	0.001	9882.73	50244.71	3746.40	51617.11	1593.45	3027.00	11428.36	7703.71	17405.43	20971.49	71.18	51617.11
6	100	25	0.25	1	0.01	15400.14	7565.97	1036.44	51771.31	421.21	1536.04	6035.30	5419.15	11148.20	17112.32	60.53	51771.31
7	100	25	0.25	2	0.001	2894.24	2589.64	3404.87	1436.64	438.02	1903.63	6035.30	2086.76	2598.64	1660.97	60.85	6035.30
8	100	25	0.9	1	0.01	3565.91	6117.96	1912.75	1641.23	421.21	1536.04	8890.19	3599.95	3460.65	2808.67	60.64	8890.19
9	1000	99	0.9	1	0.01	69975.77	49033.92	3746.40	48985.12	1593.45	3027.00	11428.36	50244.71	29754.34	27513.07	71.37	69975.77
10	100	99	0.25	1	0.01	15400.14	11696.86	1036.44	51771.31	421.21	1536.04	6035.30	5679.80	11697.14	17037.61	60.54	51771.31
11	100	25	0.9	1	0.001	2222.40	2480.80	1912.75	2844.37	421.21	1536.04	8890.19	1984.59	2786.54	2570.01	60.53	8890.19
12	1000	25	0.9	2	0.001	18673.20	11308.42	3746.40	6583.97	1593.45	2311.96	6035.30	7911.92	7270.58	5580.20	70.40	18673.20
13	100	99	0.9	1	0.001	2222.40	2480.80	1912.75	15571.38	421.21	1536.04	8890.19	4916.41	4743.90	5111.99	60.73	15571.38
14	100	99	0.25	2	0.001	7685.25	5446.95	3404.87	4501.65	438.02	1903.63	6035.30	4157.36	4196.63	2305.92	61.43	7685.25
15	100	25	0.25	1	0.001	3005.35	18684.14	1036.44	11281.08	421.21	1536.04	6035.30	4059.38	5757.37	6287.50	60.46	18684.14
16	1000	25	0.9	1	0.001	6711.63	50244.71	3746.40	10571.01	1593.45	3027.00	11428.36	7688.30	11876.36	15894.27	71.04	50244.71
17	100	25	0.9	2	0.001	2617.12	9670.54	3404.87	6096.25	438.02	1536.04	6035.30	2072.50	3983.83	3057.31	61.13	9670.54
18	1000	99	0.25	2	0.01	40093.79	18601.23	3746.40	75590.95	1593.45	3494.92	50244.71	12768.70	25766.77	26919.08	71.57	75590.95
19	100	99	0.25	2	0.01	4503.85	4598.92	3404.87	8279.76	438.02	1903.63	6035.30	6007.37	4396.47	2486.54	61.44	8279.76
20	1000	99	0.25	2	0.001	12672.70	50244.71	3746.40	9256.17	1593.45	3494.92	50244.71	50244.71	22687.22	23086.72	71.50	50244.71
21	100	99	0.9	2	0.001	2617.12	9670.54	3404.87	8279.76	438.02	1536.04	6035.30	24880.65	7107.79	7877.40	61.31	24880.65
22	100	99	0.9	2	0.01	3123.87	11405.17	3404.87	15571.38	438.02	1536.04	6035.30	49282.17	11349.60	16173.60	61.35	49282.17
23	100	99	0.9	1	0.01	8958.48	6117.96	1912.75	5650.31	421.21	1536.04	8890.19	4152.82	4704.97	3273.11	60.92	8958.48
24	100	25	0.9	2	0.01	2222.40	2364.03	3404.87	2844.37	438.02	1536.04	6035.30	5175.25	3002.54	1845.80	61.04	6035.30
25	1000	25	0.9	1	0.01	36951.37	49033.92	3746.40	36937.35	1593.45	3027.00	11428.36	49965.30	24085.39	21200.15	71.37	49965.30
26	1000	99	0.25	1	0.001	18289.68	15431.54	3746.40	12633.41	1593.45	2855.52	18289.68	15505.15	11043.10	7134.40	71.19	18289.68
27	1000	99	0.9	2	0.01	49162.28	24880.65	4172.34	25758.23	1593.45	3494.92	50950.31	50244.71	26282.11	21798.08	71.73	50950.31
28	1000	25	0.9	2	0.01	18543.40	7183.85	3746.40	8546.15	1593.45	2311.96	6035.30	6105.28	6758.22	5328.26	70.32	18543.40
29	100	25	0.25	2	0.01	4503.85	2591.24	3404.87	3632.39	438.02	1903.63	6035.30	4157.36	3333.33	1708.04	61.30	6035.30
30	1000	99	0.9	2	0.001	40488.79	49949.54	4172.34	18994.58	1593.45	3494.92	50950.31	50244.71	27486.08	22689.97	71.73	50950.31
31	1000	99	0.25	1	0.01	72749.98	15039.32	3746.40	15259.58	1593.45	2855.52	18289.68	36685.50	20777.43	23913.69	71.25	72749.98
32	1000	25	0.25	2	0.01	30416.43	18601.23	3746.40	8559.18	1593.45	2311.96	6386.34	12768.70	10547.96	9856.79	70.58	30416.43

Appendix D1 – Table 5 Full factorial data set featuring fitness (RotChr on – Gene 4 locked in first location) (GA optimisation case study).

						Seeds											
Run	POPSIZE	MAXGEN	XOVER	TOURN	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	Mean	STD	SNR	Peak
1	100	99	0.25	1	0.001	25951.12	4464.52	1446.09	10878.25	255.46	1590.86	4605.97	4499.57	6711.48	8430.60	56.89	25951.12
2	1000	25	0.25	1	0.001	13563.21	24092.50	6617.10	51595.23	1590.03	7331.27	49735.73	51056.83	25697.74	21791.19	72.54	51595.23
3	1000	25	0.25	2	0.001	7283.11	6387.37	6617.10	12576.47	1590.03	6375.27	6932.13	8894.48	7082.00	3044.83	71.82	12576.47
4	1000	25	0.25	1	0.01	18181.49	5461.15	6617.10	18266.56	1590.03	7331.27	49735.73	51056.83	19780.02	19801.04	72.24	51056.83
5	1000	99	0.9	1	0.001	29115.78	10843.85	12705.69	11310.08	1590.03	4259.21	41270.06	49644.69	20092.42	17782.45	72.26	49644.69
6	100	25	0.25	1	0.01	2840.83	36251.76	971.41	7491.27	255.46	1590.86	4605.97	4984.40	7373.99	11910.21	56.72	36251.76
7	100	25	0.25	2	0.001	4396.05	4529.74	1446.09	1438.49	329.78	1590.86	1212.13	2961.79	2238.11	1549.74	58.44	4529.74
8	100	25	0.9	1	0.01	2528.31	1937.55	950.54	4017.28	255.46	1590.86	2366.68	2961.79	2076.06	1175.82	56.58	4017.28
9	1000	99	0.9	1	0.01	36326.86	25964.51	12705.69	49509.06	1590.03	4259.21	41270.06	51056.83	27835.28	19779.65	72.40	51056.83
10	100	99	0.25	1	0.01	3837.43	36251.76	1446.09	7491.27	255.46	1590.86	4605.97	16603.86	9010.34	12172.19	56.90	36251.76
11	100	25	0.9	1	0.001	2528.31	5461.15	950.54	2818.63	255.46	1590.86	2366.68	4713.71	2585.67	1772.63	56.63	5461.15
12	1000	25	0.9	2	0.001	18192.75	2710.92	6617.10	5433.29	1590.03	6375.27	10111.93	51056.83	12761.02	16305.60	71.06	51056.83
13	100	99	0.9	1	0.001	6062.93	5461.15	1446.09	4514.47	255.46	1590.86	4464.52	4713.71	3563.65	2144.94	56.88	6062.93
14	100	99	0.25	2	0.001	8717.25	11386.57	1446.09	6972.60	329.78	1590.86	3300.53	2961.79	4588.18	3968.57	58.90	11386.57
15	100	25	0.25	1	0.001	4401.86	4360.89	971.41	4514.47	255.46	1590.86	4605.97	4499.57	3150.06	1866.70	56.72	4605.97
16	1000	25	0.9	1	0.001	29115.78	10843.85	6617.10	10728.73	1590.03	4259.21	7181.19	36765.84	13387.72	12617.04	71.94	36765.84
17	100	25	0.9	2	0.001	2414.51	2840.83	1446.09	8462.66	329.78	791.73	2831.01	23973.24	5386.23	7919.08	58.35	23973.24
18	1000	99	0.25	2	0.01	24092.87	28995.10	6617.10	72223.72	1590.03	6375.27	14764.77	51056.83	25714.46	24667.32	72.49	72223.72
19	100	99	0.25	2	0.01	25951.12	7171.57	1446.09	4017.28	329.78	1590.86	3300.53	3662.80	5933.75	8352.89	58.90	25951.12
20	1000	99	0.25	2	0.001	50193.05	12912.79	6617.10	12576.47	1590.03	6375.27	14764.77	36765.84	17724.42	16851.01	72.39	50193.05
21	100	99	0.9	2	0.001	6062.93	11691.86	1446.09	11666.90	329.78	1026.11	4514.47	23973.24	7588.92	7992.77	58.73	23973.24
22	100	99	0.9	2	0.01	25951.12	5670.68	1446.09	11638.57	329.78	1026.11	4514.47	5524.43	7012.66	8466.80	58.72	25951.12
23	100	99	0.9	1	0.01	6062.93	6732.62	1446.09	4017.28	255.46	1590.86	4464.52	4410.54	3622.54	2308.85	56.88	6732.62
24	100	25	0.9	2	0.01	2695.33	1579.32	1446.09	3714.00	329.78	791.73	2831.01	1647.44	1879.34	1124.60	58.11	3714.00
25	1000	25	0.9	1	0.01	36326.86	12650.96	6617.10	49029.11	1590.03	4259.21	7181.19	51056.83	21088.91	20868.39	72.04	51056.83
26	1000	99	0.25	1	0.001	18218.84	51495.57	6617.10	51595.23	1590.03	9797.36	49735.73	51056.83	30013.34	22872.72	72.66	51595.23
27	1000	99	0.9	2	0.01	35616.87	49744.95	6617.10	26451.49	1590.03	6375.27	10111.93	24126.41	20079.26	16855.20	72.43	49744.95
28	1000	25	0.9	2	0.01	8232.54	14782.98	6617.10	9391.52	1590.03	6375.27	10111.93	8106.54	8150.99	3740.29	72.05	14782.98
29	100	25	0.25	2	0.01	1718.40	1034.34	1446.09	2174.61	329.78	1590.86	1212.13	3662.80	1646.13	977.61	58.13	3662.80
30	1000	99	0.9	2	0.001	18192.75	10843.85	6617.10	11425.15	1590.03	6375.27	10111.93	51056.83	14526.62	15523.85	72.29	51056.83
31	1000	99	0.25	1	0.01	24126.41	18209.42	6617.10	52154.35	1590.03	9797.36	49735.73	51056.83	26660.90	21280.63	72.65	52154.35
32	1000	25	0.25	2	0.01	4776.71	28995.10	6617.10	6613.74	1590.03	6375.27	6932.13	6398.14	8537.28	8452.74	71.58	28995.10

Appendix D1 – Table 6 Full factorial data set featuring fitness (RotChr on – Gene 5 locked in first location) (GA optimisation case study).

Run	POPSIZE	MAXGEN	XOVER	TOURN	MUTPRO	Seeds								Mean	STD	SNR	Peak
						0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958				
1	100	99	0.25	1	0.001	6042.62	5897.80	2249.41	5638.60	255.42	1587.26	3273.73	4693.45	3704.79	2193.43	56.95	6042.62
2	1000	25	0.25	1	0.001	26546.09	7200.31	9500.65	67043.14	1589.37	20788.70	19116.33	8980.85	20095.68	20673.24	72.54	67043.14
3	1000	25	0.25	2	0.001	10538.70	10794.07	9500.65	5423.10	1589.37	67043.14	8058.68	26647.55	17449.41	21326.50	72.26	67043.14
4	1000	25	0.25	1	0.01	8429.31	18219.72	9500.65	11648.86	1589.37	20788.70	19116.33	8588.81	12235.22	6603.71	72.50	20788.70
5	1000	99	0.9	1	0.001	50554.79	49653.29	9500.65	51398.92	1589.37	20788.70	15296.49	37227.37	29501.20	20161.27	72.85	51398.92
6	100	25	0.25	1	0.01	6042.62	15362.16	2249.41	2603.42	255.42	979.53	2808.26	5183.68	4435.56	4821.60	56.75	15362.16
7	100	25	0.25	2	0.001	2349.73	1830.96	2249.41	6655.75	255.42	1587.26	3288.44	4601.60	2852.32	1989.97	56.84	6655.75
8	100	25	0.9	1	0.01	6042.62	7130.87	2249.41	2456.92	255.42	1587.26	1933.39	4601.60	3282.19	2383.70	56.87	7130.87
9	1000	99	0.9	1	0.01	15012.25	8024.52	9500.65	52878.11	1589.37	20788.70	15296.49	11551.84	16830.24	15639.63	72.58	52878.11
10	100	99	0.25	1	0.01	6042.62	15362.16	2249.41	2854.03	255.42	1587.26	3273.73	5183.68	4601.04	4728.80	56.93	15362.16
11	100	25	0.9	1	0.001	1463.99	7130.87	2249.41	4495.41	255.42	1587.26	1933.39	4081.64	2899.67	2203.20	56.78	7130.87
12	1000	25	0.9	2	0.001	4687.53	5082.53	9500.65	4315.51	1589.37	2352.57	7645.99	4129.68	4912.98	2595.83	69.99	9500.65
13	100	99	0.9	1	0.001	18563.37	7130.87	2249.41	5250.94	255.42	1587.26	2957.79	4081.64	5259.59	5791.21	56.95	18563.37
14	100	99	0.25	2	0.001	18841.55	3328.42	2249.41	6655.75	255.42	1587.26	4015.28	4601.60	5191.84	5851.52	56.95	18841.55
15	100	25	0.25	1	0.001	3174.91	2941.56	2249.41	2185.30	255.42	979.53	2808.26	2388.45	2122.85	1009.37	56.65	3174.91
16	1000	25	0.9	1	0.001	6396.65	19043.48	9500.65	51398.92	1589.37	20788.70	15296.49	15362.16	17422.05	15175.80	72.54	51398.92
17	100	25	0.9	2	0.001	4374.51	2192.63	2249.41	3569.72	255.42	1078.76	2808.26	4245.75	2596.81	1460.97	56.75	4374.51
18	1000	99	0.25	2	0.01	51398.92	15451.06	9500.65	51398.92	1589.37	67043.14	52878.11	14727.68	32998.48	25104.94	72.83	67043.14
19	100	99	0.25	2	0.01	3869.37	7169.34	2249.41	6641.33	255.42	1587.26	4015.28	4693.45	3810.11	2394.60	56.95	7169.34
20	1000	99	0.25	2	0.001	18305.02	10794.07	9500.65	11648.86	1589.37	67043.14	52878.11	50574.51	27791.72	24927.59	72.73	67043.14
21	100	99	0.9	2	0.001	6042.62	7278.42	2249.41	8576.75	255.42	1424.29	10807.42	4245.75	5110.01	3705.83	56.95	10807.42
22	100	99	0.9	2	0.01	2743.06	18219.72	2249.41	3772.23	255.42	1424.29	10807.42	2552.59	5253.02	6134.54	56.89	18219.72
23	100	99	0.9	1	0.01	67663.77	7130.87	2249.41	15260.82	255.42	1587.26	2957.79	4601.60	12713.37	22698.83	56.96	67663.77
24	100	25	0.9	2	0.01	2100.77	1068.03	2249.41	3569.72	255.42	1078.76	2808.26	1608.99	1842.42	1062.66	56.46	3569.72
25	1000	25	0.9	1	0.01	15012.25	5872.08	9500.65	11101.42	1589.37	20788.70	15296.49	11551.84	11339.10	5938.68	72.38	20788.70
26	1000	99	0.25	1	0.001	68321.73	50518.65	9500.65	67043.14	1589.37	20788.70	19116.33	52390.45	36158.63	26431.47	72.87	68321.73
27	1000	99	0.9	2	0.01	18212.58	29065.98	9500.65	52878.11	1589.37	2352.57	15527.88	37687.07	20851.78	17944.38	71.27	52878.11
28	1000	25	0.9	2	0.01	5791.60	29065.98	9500.65	18438.31	1589.37	2352.57	7645.99	5791.60	10022.01	9297.82	70.78	29065.98
29	100	25	0.25	2	0.01	1690.82	3697.64	2249.41	1150.14	255.42	1587.26	3288.44	1368.43	1910.94	1132.10	56.54	3697.64
30	1000	99	0.9	2	0.001	10933.99	37574.28	9500.65	18341.05	1589.37	2352.57	15527.88	11351.43	13396.40	11341.18	71.17	37574.28
31	1000	99	0.25	1	0.01	9398.25	18219.72	9500.65	47608.38	1589.37	20788.70	19116.33	8994.94	16902.04	14003.63	72.60	47608.38
32	1000	25	0.25	2	0.01	8385.03	15296.49	9500.65	51398.92	1589.37	67043.14	8058.68	11698.82	21621.39	23891.54	72.51	67043.14

Appendix D1 – Table 7 Full factorial data set featuring fitness (RotChr on – Gene 6 locked in first location) (GA optimisation case study).

						Seeds											
Run	**POPSIZE**	**MAXGEN**	**XOVER**	**TOURN**	**MUTPRO**	**0.0251**	**0.152**	**0.253**	**0.4174**	**0.54**	**0.756**	**0.8757**	**0.958**	**Mean**	**STD**	**SNR**	**Peak**
1	100	99	0.25	1	0.001	6066.53	4696.77	2093.04	3394.26	378.19	938.78	3477.78	5658.73	3338.01	2096.47	59.67	6066.53
2	1000	25	0.25	1	0.001	70853.73	7385.80	2935.81	8584.54	1591.51	5630.44	4804.27	8989.90	13847.00	23180.45	71.04	70853.73
3	1000	25	0.25	2	0.001	7959.09	8946.81	8916.84	8572.80	1591.51	4905.31	9473.49	8292.71	7332.32	2709.85	71.90	9473.49
4	1000	25	0.25	1	0.01	6534.86	12717.76	2935.81	9875.73	1591.51	5630.44	4804.27	10065.84	6769.53	3828.83	71.00	12717.76
5	1000	99	0.9	1	0.001	18552.67	51180.94	4600.79	25917.03	1591.51	2408.70	50479.01	51082.16	25726.60	22448.47	71.11	51180.94
6	100	25	0.25	1	0.01	4615.95	2552.72	2093.04	2115.47	378.19	938.78	2806.20	2510.28	2251.33	1272.35	59.46	4615.95
7	100	25	0.25	2	0.001	1168.12	5226.05	1130.00	5448.06	378.19	1692.18	1142.89	2261.39	2305.86	1946.61	59.08	5448.06
8	100	25	0.9	1	0.01	4615.95	6335.75	1130.00	3126.59	378.19	1692.18	3005.16	2084.36	2796.02	1939.86	59.67	6335.75
9	1000	99	0.9	1	0.01	7651.19	15052.43	4600.79	52145.71	1591.51	2408.70	50479.01	51082.16	23126.44	23642.13	70.99	52145.71
10	100	99	0.25	1	0.01	4615.95	6637.07	2093.04	4260.15	378.19	938.78	3477.78	4506.31	3363.41	2098.07	59.68	6637.07
11	100	25	0.9	1	0.001	6066.53	6335.75	1130.00	3292.80	378.19	1692.18	3005.16	2467.63	3046.03	2170.06	59.71	6335.75
12	1000	25	0.9	2	0.001	6111.57	3938.44	4600.79	7734.87	1591.51	2958.72	2371.51	18593.03	5987.56	5472.83	69.76	18593.03
13	100	99	0.9	1	0.001	6066.53	6382.49	2093.04	3292.80	378.19	1692.18	3368.11	4050.90	3415.53	2076.95	60.08	6382.49
14	100	99	0.25	2	0.001	6066.53	5226.05	1130.00	15259.98	378.19	1692.18	2371.51	4621.76	4593.28	4772.90	59.78	15259.98
15	100	25	0.25	1	0.001	2535.16	4696.77	2093.04	3394.26	378.19	938.78	2806.20	1557.38	2299.97	1383.27	59.40	4696.77
16	1000	25	0.9	1	0.001	7172.17	8553.94	4600.79	15259.98	1591.51	2408.70	50479.01	26216.33	14535.30	16614.13	70.88	50479.01
17	100	25	0.9	2	0.001	2085.07	2900.66	2597.88	3735.28	378.19	1649.06	2371.51	3639.50	2419.64	1092.68	59.90	3735.28
18	1000	99	0.25	2	0.01	50148.12	18552.67	8916.84	48816.21	1591.51	4905.31	13455.91	10846.52	19654.14	19110.92	72.34	50148.12
19	100	99	0.25	2	0.01	5902.37	2197.84	1130.00	6548.15	378.19	4905.31	2371.51	10161.83	4199.40	3291.46	59.86	10161.83
20	1000	99	0.25	2	0.001	16511.23	37567.24	8916.84	15278.78	1591.51	4905.31	13455.91	51082.16	18663.62	17017.92	72.37	51082.16
21	100	99	0.9	2	0.001	6382.49	2957.84	2597.88	7955.48	378.19	1521.90	2388.86	5008.90	3648.94	2570.72	60.03	7955.48
22	100	99	0.9	2	0.01	6066.53	7617.85	2597.88	3554.76	378.19	1521.90	2388.86	6406.77	3816.59	2588.47	60.06	7617.85
23	100	99	0.9	1	0.01	4615.95	51082.16	2093.04	3150.43	378.19	1692.18	3368.11	3942.67	8790.34	17141.16	60.07	51082.16
24	100	25	0.9	2	0.01	6066.53	2595.96	2597.88	2563.44	378.19	740.43	2371.51	6406.77	2965.09	2200.33	59.26	6406.77
25	1000	25	0.9	1	0.01	4591.23	10185.49	4600.79	8518.52	1591.51	2408.70	50479.01	26192.95	13571.03	16851.07	70.66	50479.01
26	1000	99	0.25	1	0.001	70853.73	18552.67	3553.33	9714.29	1591.51	5630.44	51828.08	9473.49	21399.69	25684.91	71.78	70853.73
27	1000	99	0.9	2	0.01	15250.38	11382.56	4600.79	52145.71	1591.51	4905.31	51828.08	26192.95	20987.16	20624.56	72.06	52145.71
28	1000	25	0.9	2	0.01	5173.93	3944.79	4600.79	15259.98	1591.51	2958.72	2371.51	11439.59	5917.60	4840.25	69.75	15259.98
29	100	25	0.25	2	0.01	4417.10	2164.48	1130.00	2074.14	378.19	1692.18	1142.89	3794.73	2099.22	1374.97	59.27	4417.10
30	1000	99	0.9	2	0.001	16511.23	14658.21	4600.79	49587.03	1591.51	4905.31	51828.08	51082.16	24345.54	22513.53	72.10	51828.08
31	1000	99	0.25	1	0.01	11663.75	18246.62	3553.33	11617.50	1591.51	5630.44	51828.08	51082.16	19401.68	20476.28	71.84	51828.08
32	1000	25	0.25	2	0.01	7006.06	5188.05	8916.84	7734.87	1591.51	4905.31	9473.49	10846.52	6957.83	2976.97	71.68	10846.52

Appendix D1 – Table 8 Full factorial data set featuring fitness (RotChr on – Gene 7 locked in first location) (GA optimisation case study).

Run	POPSIZE	MAXGEN	XOVER	TOURN	MUTPRO	Seeds								Mean	STD	SNR	Peak
						0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958				
1	100	99	0.25	1	0.001	5304.37	18238.23	804.72	12754.44	437.25	1840.80	8927.36	3600.37	6488.44	6364.34	60.46	18238.23
2	1000	25	0.25	1	0.001	12590.86	10195.38	4586.42	8927.36	3920.65	71108.99	6702.74	25632.78	17958.15	22542.26	76.85	71108.99
3	1000	25	0.25	2	0.001	16513.59	6670.60	6671.86	8902.92	3920.65	71108.99	5112.72	51382.91	21285.53	25507.94	76.85	71108.99
4	1000	25	0.25	1	0.01	7184.16	18829.17	4586.42	18454.51	3920.65	71108.99	6702.74	51382.91	22771.19	25004.36	76.97	71108.99
5	1000	99	0.9	1	0.001	35915.24	12555.18	4586.42	38014.98	3920.65	71108.99	40250.16	38014.98	30545.82	22635.01	78.17	71108.99
6	100	25	0.25	1	0.01	5602.93	3114.71	804.72	10536.49	437.25	1589.47	8927.36	2547.50	4195.05	3796.18	60.29	10536.49
7	100	25	0.25	2	0.001	2603.37	6340.76	2019.18	1251.55	437.25	1589.47	6049.57	6439.86	3341.38	2509.83	60.75	6439.86
8	100	25	0.9	1	0.01	7991.94	2597.24	804.72	3563.57	437.25	1589.47	6049.57	3005.62	3254.92	2606.47	60.25	7991.94
9	1000	99	0.9	1	0.01	25728.52	18208.63	4586.42	51295.29	3920.65	71108.99	40250.16	51382.91	33310.20	24205.49	78.29	71108.99
10	100	99	0.25	1	0.01	52076.58	8571.23	804.72	10536.49	437.25	1840.80	8927.36	5017.52	11026.49	17041.49	60.49	52076.58
11	100	25	0.9	1	0.001	3926.97	5087.43	804.72	3563.57	437.25	1589.47	6049.57	25632.78	5886.47	8227.13	60.35	25632.78
12	1000	25	0.9	2	0.001	5511.62	15248.47	4586.42	12704.94	3920.65	71108.99	8902.10	15464.24	17180.93	22277.86	76.65	71108.99
13	100	99	0.9	1	0.001	4497.02	6187.91	804.72	6649.01	437.25	1589.47	6049.57	25632.78	6480.97	8138.98	60.40	25632.78
14	100	99	0.25	2	0.001	6300.63	18238.23	2019.18	6130.46	437.25	1589.47	6049.57	6439.86	5900.58	5558.04	61.27	18238.23
15	100	25	0.25	1	0.001	5304.37	5612.59	804.72	3563.57	437.25	1589.47	8927.36	2739.06	3622.30	2876.84	60.30	8927.36
16	1000	25	0.9	1	0.001	6314.27	12555.18	4586.42	13351.73	3920.65	71108.99	40250.16	38014.98	23762.80	23953.87	77.24	71108.99
17	100	25	0.9	2	0.001	1716.64	3259.08	2591.27	1089.91	389.43	1589.47	6049.57	4102.62	2598.50	1834.60	59.74	6049.57
18	1000	99	0.25	2	0.01	25773.11	49065.42	6671.86	25955.84	3920.65	71108.99	48325.91	51382.91	35275.59	23550.58	79.40	71108.99
19	100	99	0.25	2	0.01	5610.37	5090.69	2019.18	5907.38	437.25	71108.99	6049.57	35786.26	16501.21	24761.66	61.55	71108.99
20	1000	99	0.25	2	0.001	48546.99	18207.71	6671.86	37754.84	3920.65	71108.99	48325.91	51382.91	35739.98	23865.57	79.36	71108.99
21	100	99	0.9	2	0.001	5481.35	5683.62	2591.27	5550.21	389.43	1589.47	37553.60	9475.31	8539.28	12066.75	60.43	37553.60
22	100	99	0.9	2	0.01	3926.97	6651.58	2591.27	6650.09	389.43	1589.47	37553.60	5576.13	8116.07	12116.59	60.41	37553.60
23	100	99	0.9	1	0.01	7991.94	5879.64	804.72	50503.12	437.25	1589.47	6049.57	25632.78	12361.06	17417.73	60.43	50503.12
24	100	25	0.9	2	0.01	1891.35	5816.92	2591.27	3450.82	389.43	1589.47	6049.57	1392.07	2896.36	2074.97	59.96	6049.57
25	1000	25	0.9	1	0.01	8031.09	6338.29	4586.42	51295.29	3920.65	71108.99	40250.16	8990.28	24315.14	26185.78	76.82	71108.99
26	1000	99	0.25	1	0.001	12590.86	25955.84	4586.42	49360.04	3920.65	71108.99	13399.52	51382.91	29038.15	25172.49	77.99	71108.99
27	1000	99	0.9	2	0.01	18544.52	15340.62	4586.42	50552.73	3920.65	71108.99	10063.64	69363.36	30435.12	28610.41	77.88	71108.99
28	1000	25	0.9	2	0.01	4261.99	3390.40	4586.42	11558.63	3920.65	71108.99	8902.10	49323.48	19631.58	25870.61	74.63	71108.99
29	100	25	0.25	2	0.01	3000.47	1580.75	2019.18	2189.90	437.25	1589.47	6049.57	2743.21	2451.22	1653.85	60.74	6049.57
30	1000	99	0.9	2	0.001	25728.52	25773.11	4586.42	19135.09	3920.65	71108.99	10063.64	51382.91	26462.42	23678.39	77.93	71108.99
31	1000	99	0.25	1	0.01	71108.99	18829.17	4586.42	49065.42	3920.65	71108.99	13399.52	51382.91	35425.26	28514.40	78.16	71108.99
32	1000	25	0.25	2	0.01	6117.44	6619.68	6671.86	10846.74	3920.65	71108.99	5112.72	51382.91	20222.62	25939.43	76.37	71108.99

Appendix D1 – Table 9 Full factorial data set featuring fitness (RotChr on – Gene 8 locked in first location) (GA optimisation case study).

						Seeds											
Run	**POPSIZE**	**MAXGEN**	**XOVER**	**TOURN**	**MUTPRO**	**0.0251**	**0.152**	**0.253**	**0.4174**	**0.54**	**0.756**	**0.8757**	**0.958**	**Mean**	**STD**	**SNR**	**Peak**
1	100	99	0.25	1	0.001	4405.38	6090.82	1422.99	7820.92	336.77	4952.11	6001.50	4765.28	4474.47	2475.38	59.25	7820.92
2	1000	25	0.25	1	0.001	5693.25	41990.96	9383.12	51587.57	1592.90	2595.38	8212.86	4327.10	15672.89	19549.59	70.88	51587.57
3	1000	25	0.25	2	0.001	48874.57	5179.57	9383.12	6354.52	1592.90	53714.52	51523.00	4504.63	22640.85	23921.92	71.89	53714.52
4	1000	25	0.25	1	0.01	6058.08	15520.44	9383.12	7190.43	1592.90	2595.38	8212.86	10953.86	7688.38	4490.48	71.05	15520.44
5	1000	99	0.9	1	0.001	16319.64	48522.71	9383.12	51330.22	1592.90	2595.38	6646.53	25839.96	20278.81	19910.27	71.38	51330.22
6	100	25	0.25	1	0.01	3313.91	4614.48	1422.99	4510.03	336.77	4952.11	3322.18	3451.43	3240.49	1613.37	59.16	4952.11
7	100	25	0.25	2	0.001	4405.38	1631.81	710.01	3284.13	702.36	4952.11	1088.76	2486.29	2407.61	1663.52	61.57	4952.11
8	100	25	0.9	1	0.01	7136.97	5444.68	895.11	3036.04	802.02	992.01	1198.69	7799.55	3413.13	2959.27	62.32	7799.55
9	1000	99	0.9	1	0.01	29859.62	68047.59	9383.12	37290.45	1592.90	2595.38	6646.53	26378.11	22724.21	22737.09	71.40	68047.59
10	100	99	0.25	1	0.01	4159.01	8469.86	1422.99	6083.46	336.77	4952.11	6001.50	25839.96	7158.21	7986.67	59.26	25839.96
11	100	25	0.9	1	0.001	6051.55	10077.60	895.11	3000.95	802.02	992.01	1198.69	3042.85	3257.60	3282.28	62.24	10077.60
12	1000	25	0.9	2	0.001	10116.21	68047.59	9383.12	15092.76	1592.90	4952.11	8897.77	3829.12	15238.95	21750.98	71.70	68047.59
13	100	99	0.9	1	0.001	6051.55	10077.60	895.11	3000.95	802.02	4952.11	6425.65	19466.52	6458.94	6090.32	64.23	19466.52
14	100	99	0.25	2	0.001	4405.38	5881.29	895.11	3284.13	702.36	4952.11	19037.55	25839.96	8124.74	9201.25	63.60	25839.96
15	100	25	0.25	1	0.001	4405.38	4614.48	1422.99	1389.34	336.77	4952.11	3322.18	4765.28	3151.07	1836.29	58.99	4952.11
16	1000	25	0.9	1	0.001	7767.18	6916.67	9383.12	51330.22	1592.90	2595.38	6001.50	24212.31	13724.91	16714.18	71.10	51330.22
17	100	25	0.9	2	0.001	6051.55	4999.86	879.30	3319.61	702.36	1206.38	5796.92	2430.06	3173.26	2214.06	62.63	6051.55
18	1000	99	0.25	2	0.01	19243.35	18346.80	9383.12	52624.43	1592.90	53714.52	51880.88	26378.11	29145.51	20852.59	72.86	53714.52
19	100	99	0.25	2	0.01	9544.00	3771.45	895.11	4365.12	702.36	53714.52	19037.55	25839.96	14733.76	18143.76	63.70	53714.52
20	1000	99	0.25	2	0.001	48874.57	68047.59	9383.12	24183.42	1592.90	53714.52	51880.88	25839.96	35439.62	23578.02	72.90	68047.59
21	100	99	0.9	2	0.001	6051.55	8673.95	895.11	3319.61	702.36	1206.38	6001.50	3452.07	3787.82	2897.85	62.79	8673.95
22	100	99	0.9	2	0.01	6051.55	8673.95	895.11	3888.78	702.36	1206.38	6001.50	9410.31	4603.74	3479.48	62.89	9410.31
23	100	99	0.9	1	0.01	7136.97	5444.68	895.11	4259.48	802.02	4952.11	6425.65	7799.55	4714.45	2645.91	64.27	7799.55
24	100	25	0.9	2	0.01	6051.55	8673.95	879.30	2160.42	702.36	1206.38	5796.92	9410.31	4360.15	3572.09	62.69	9410.31
25	1000	25	0.9	1	0.01	26126.38	16183.38	9383.12	6740.26	1592.90	2595.38	6001.50	25839.96	11807.86	9823.83	71.17	26126.38
26	1000	99	0.25	1	0.001	7593.34	41990.96	9383.12	52373.89	1592.90	2595.38	51880.88	51330.22	27342.59	23924.65	71.45	52373.89
27	1000	99	0.9	2	0.01	18346.80	9317.90	9383.12	11941.81	1592.90	4952.11	16519.39	24183.42	12029.68	7379.13	72.28	24183.42
28	1000	25	0.9	2	0.01	18346.80	8079.92	9383.12	11404.02	1592.90	4952.11	8897.77	24183.42	10855.01	7254.59	72.16	24183.42
29	100	25	0.25	2	0.01	2709.63	2943.50	710.01	3833.36	702.36	4952.11	1088.76	3451.43	2548.90	1574.10	61.79	4952.11
30	1000	99	0.9	2	0.001	18307.48	68047.59	9383.12	24306.67	1592.90	4952.11	16519.39	15460.65	19821.24	20840.98	72.41	68047.59
31	1000	99	0.25	1	0.01	19037.55	26126.38	9383.12	50615.16	1592.90	2595.38	51880.88	24212.31	23180.46	19579.21	71.54	51880.88
32	1000	25	0.25	2	0.01	19229.57	9746.02	9383.12	52624.43	1592.90	53714.52	51523.00	24212.31	27753.23	21675.67	72.78	53714.52

Appendix D1 – Table 10 Full factorial data set featuring fitness (RotChr on – Gene 9 locked in first location) (GA optimisation case study).

						Seeds											
Run	**POPSIZE**	**MAXGEN**	**XOVER**	**TOURN**	**MUTPRO**	**0.0251**	**0.152**	**0.253**	**0.4174**	**0.54**	**0.756**	**0.8757**	**0.958**	**Mean**	**STD**	**SNR**	**Peak**
1	100	99	0.25	1	0.001	7031.95	6991.51	6418.16	12624.04	2706.40	1535.89	5888.72	4886.85	6010.44	3340.82	70.57	12624.04
2	1000	25	0.25	1	0.001	69193.01	6604.98	6596.60	6617.37	2706.40	7575.21	24577.83	7764.70	16454.51	22302.03	75.21	69193.01
3	1000	25	0.25	2	0.001	49058.75	6687.03	6460.18	8971.05	2706.40	2597.14	6073.28	7764.70	11289.82	15423.81	73.15	49058.75
4	1000	25	0.25	1	0.01	74560.82	8570.08	6596.60	19113.21	2706.40	7575.21	24577.83	11761.87	19432.75	23383.93	75.97	74560.82
5	1000	99	0.9	1	0.001	14626.27	13626.61	6460.18	50031.57	2706.40	2600.57	18306.91	51225.59	19948.01	19764.36	73.95	51225.59
6	100	25	0.25	1	0.01	4414.03	3913.23	2097.13	3327.12	2706.40	1535.89	3323.57	26019.46	5917.10	8175.83	68.67	26019.46
7	100	25	0.25	2	0.001	2531.06	8937.79	1394.69	2538.45	2706.40	1535.89	6026.85	2964.00	3579.39	2590.50	67.16	8937.79
8	100	25	0.9	1	0.01	6051.17	2596.50	1714.45	2426.59	751.90	1649.06	6342.21	2964.00	3061.98	2051.96	64.32	6342.21
9	1000	99	0.9	1	0.01	13423.32	50031.57	6460.18	18579.58	2706.40	2600.57	18306.91	50997.85	20388.30	19620.79	73.97	50997.85
10	100	99	0.25	1	0.01	6051.17	4776.67	6418.16	49319.54	2706.40	1535.89	5888.72	26019.46	12839.50	16628.69	70.66	49319.54
11	100	25	0.9	1	0.001	2409.55	7257.06	1714.45	2932.69	751.90	1649.06	6342.21	2964.00	3252.62	2319.74	64.37	7257.06
12	1000	25	0.9	2	0.001	9000.87	5693.64	6596.60	37714.00	2706.40	2633.31	7601.50	11414.00	10420.04	11420.51	73.32	37714.00
13	100	99	0.9	1	0.001	5611.79	7257.06	1714.45	3784.07	751.90	1649.06	8948.10	26019.46	6966.99	8224.27	64.86	26019.46
14	100	99	0.25	2	0.001	5637.52	15226.79	1394.69	4167.92	2706.40	1535.89	6026.85	4710.82	5175.86	4421.31	68.10	15226.79
15	100	25	0.25	1	0.001	5568.90	2651.55	2097.13	4006.83	2706.40	1535.89	3323.57	4710.82	3325.14	1360.95	68.39	5568.90
16	1000	25	0.9	1	0.001	13423.32	11465.22	6460.18	15272.90	2706.40	2600.57	6962.94	26019.46	10613.87	7791.75	73.62	26019.46
17	100	25	0.9	2	0.001	1565.23	3491.08	1714.45	7206.45	2706.40	1649.06	2782.43	3189.49	3038.07	1837.29	67.04	7206.45
18	1000	99	0.25	2	0.01	52481.01	28834.32	6460.18	71954.70	2706.40	4154.22	36711.30	26404.14	28713.28	24723.46	75.56	71954.70
19	100	99	0.25	2	0.01	7922.37	10097.67	1394.69	5057.68	2706.40	1535.89	6026.85	4504.67	4905.78	3071.01	68.18	10097.67
20	1000	99	0.25	2	0.001	49058.75	8449.78	6460.18	42000.24	2706.40	4154.22	36711.30	50233.87	24971.84	21350.52	75.33	50233.87
21	100	99	0.9	2	0.001	5611.79	8943.19	1714.45	7206.45	2706.40	1844.99	9522.50	3931.09	5185.11	3119.58	69.44	9522.50
22	100	99	0.9	2	0.01	8659.63	15166.37	1714.45	15508.63	2706.40	1844.99	9522.50	4886.85	7501.23	5651.87	69.76	15508.63
23	100	99	0.9	1	0.01	6051.17	4496.43	1714.45	3197.56	751.90	1649.06	8948.10	4885.93	3961.83	2716.49	64.71	8948.10
24	100	25	0.9	2	0.01	8659.63	15166.37	1714.45	4517.26	2706.40	1649.06	2782.43	3488.36	5085.50	4650.80	68.53	15166.37
25	1000	25	0.9	1	0.01	8973.68	18284.08	6460.18	9829.64	2706.40	2600.57	6962.94	20936.48	9594.25	6736.89	73.50	20936.48
26	1000	99	0.25	1	0.001	69193.01	50997.85	6596.60	16563.60	2706.40	7575.21	24577.83	69193.01	30925.44	28060.42	76.41	69193.01
27	1000	99	0.9	2	0.01	16637.96	49731.41	6596.60	9829.64	2706.40	2633.31	24708.44	51225.59	20508.67	19907.48	73.98	51225.59
28	1000	25	0.9	2	0.01	6051.17	8659.63	6596.60	6661.43	2706.40	2633.31	7601.50	51225.59	11516.95	16188.52	73.18	51225.59
29	100	25	0.25	2	0.01	1720.31	6340.36	1394.69	4377.45	2706.40	1535.89	6026.85	3191.12	3411.63	1976.39	66.95	6340.36
30	1000	99	0.9	2	0.001	48833.66	15373.30	6596.60	50793.60	2706.40	2633.31	24708.44	11414.00	20382.41	19552.39	74.01	50793.60
31	1000	99	0.25	1	0.01	74560.82	18284.08	6596.60	19113.21	2706.40	7575.21	24577.83	51225.59	25579.97	24958.86	76.36	74560.82
32	1000	25	0.25	2	0.01	11360.94	6683.18	6460.18	8948.10	2706.40	2597.14	6073.28	14616.09	7430.66	4112.78	73.20	14616.09

Appendix D1 – Table 11 Full factorial data set featuring fitness (RotChr on – Gene 10 locked in first location) (GA optimisation case study).

						Seeds											
Run	**POPSIZE**	**MAXGEN**	**XOVER**	**TOURN**	**MUTPRO**	**0.0251**	**0.152**	**0.253**	**0.4174**	**0.54**	**0.756**	**0.8757**	**0.958**	**Mean**	**STD**	**SNR**	**Peak**
1	100	99	0.25	1	0.001	5514.20	10870.87	3806.85	7640.32	255.47	2682.41	36757.29	6117.08	9205.56	11583.78	57.10	36757.29
2	1000	25	0.25	1	0.001	18574.21	8693.67	9498.85	15631.21	1591.88	3484.51	7153.29	7759.65	9048.41	5684.72	71.67	18574.21
3	1000	25	0.25	2	0.001	8033.72	8943.73	41469.05	18272.37	1591.88	4167.51	18391.66	50330.73	18900.08	17855.47	72.15	50330.73
4	1000	25	0.25	1	0.01	11762.42	11344.34	9498.85	52252.10	1591.88	3484.51	7153.29	50330.73	18427.26	20598.45	71.84	52252.10
5	1000	99	0.9	1	0.001	26800.59	26480.55	9498.85	52992.55	1591.88	4270.08	50348.50	15446.39	23428.67	19715.98	72.33	52992.55
6	100	25	0.25	1	0.01	6059.20	2502.97	3806.85	3570.82	255.47	2682.41	2506.95	2961.50	3043.27	1623.29	56.97	6059.20
7	100	25	0.25	2	0.001	5514.20	19188.96	1136.94	2461.04	255.47	1744.21	5794.00	3647.85	4967.83	6077.15	56.80	19188.96
8	100	25	0.9	1	0.01	6059.20	5541.70	3806.85	52252.10	255.47	2682.41	6016.61	3560.64	10021.87	17174.87	57.07	52252.10
9	1000	99	0.9	1	0.01	26693.73	50330.73	9498.85	68024.76	1591.88	4270.08	50348.50	69089.55	34981.01	28038.42	72.37	69089.55
10	100	99	0.25	1	0.01	6059.20	9796.27	3806.85	52992.55	255.47	2682.41	36757.29	4879.09	14653.64	19345.41	57.10	52992.55
11	100	25	0.9	1	0.001	3002.85	3940.65	3806.85	6649.65	255.47	2682.41	6016.61	2588.59	3617.88	2024.99	57.02	6649.65
12	1000	25	0.9	2	0.001	11111.16	6664.42	9498.85	15149.87	1591.88	3484.51	9318.84	18458.05	9409.70	5625.15	71.73	18458.05
13	100	99	0.9	1	0.001	6617.32	15394.70	3806.85	6649.65	255.47	2682.41	6016.61	6414.23	5979.65	4440.85	57.09	15394.70
14	100	99	0.25	2	0.001	5514.20	19188.96	3806.85	8974.01	255.47	2319.39	9001.61	4879.09	6742.45	5858.35	57.08	19188.96
15	100	25	0.25	1	0.001	2557.21	10870.87	3806.85	5172.82	255.47	2682.41	2506.95	2961.50	3851.76	3153.07	56.99	10870.87
16	1000	25	0.9	1	0.001	18458.05	18464.51	9498.85	19245.84	1591.88	4270.08	9567.61	12794.58	11736.42	6722.32	72.16	19245.84
17	100	25	0.9	2	0.001	4472.99	3371.68	3806.85	4401.13	255.47	2682.41	2589.66	4384.45	3245.58	1422.17	57.01	4472.99
18	1000	99	0.25	2	0.01	15287.04	18464.51	41469.05	68373.36	1591.88	4167.51	37047.97	50164.51	29570.73	23551.58	72.39	68373.36
19	100	99	0.25	2	0.01	6059.20	4618.46	3806.85	8569.99	255.47	2319.39	9001.61	26855.46	7685.80	8290.25	57.08	26855.46
20	1000	99	0.25	2	0.001	50164.51	26480.55	41469.05	26480.55	1591.88	4167.51	37047.97	50330.73	29716.59	18896.82	72.43	50330.73
21	100	99	0.9	2	0.001	5541.70	3371.68	3806.85	9498.85	255.47	2818.88	5880.87	4674.66	4481.12	2688.70	57.07	9498.85
22	100	99	0.9	2	0.01	6721.62	6092.22	3806.85	3570.82	255.47	2818.88	5880.87	7779.21	4615.74	2455.60	57.07	7779.21
23	100	99	0.9	1	0.01	18205.67	5541.70	3806.85	52992.55	255.47	2682.41	6016.61	11658.26	12644.94	17258.86	57.10	52992.55
24	100	25	0.9	2	0.01	6721.62	4719.23	3806.85	2598.67	255.47	2682.41	2589.66	3784.78	3394.83	1881.82	57.00	6721.62
25	1000	25	0.9	1	0.01	11762.42	50330.73	9498.85	10093.26	1591.88	4270.08	9567.61	26855.46	15496.28	15928.78	72.13	50330.73
26	1000	99	0.25	1	0.001	51954.48	49424.70	9498.85	52992.55	1591.88	3484.51	7779.21	10133.78	23357.49	23463.69	71.91	52992.55
27	1000	99	0.9	2	0.01	50288.22	51954.48	9498.85	52992.55	1591.88	3484.51	10820.71	50330.73	28870.24	24271.18	72.06	52992.55
28	1000	25	0.9	2	0.01	6947.92	8964.23	9498.85	5571.94	1591.88	3484.51	9318.84	50330.73	11963.61	15764.25	71.51	50330.73
29	100	25	0.25	2	0.01	6059.20	3407.51	1136.94	1530.98	255.47	1744.21	5794.00	2569.97	2812.28	2137.18	56.69	6059.20
30	1000	99	0.9	2	0.001	13463.72	49087.52	9498.85	16364.60	1591.88	3484.51	10820.71	50164.51	19309.54	19325.26	71.98	50164.51
31	1000	99	0.25	1	0.01	26800.59	69089.55	9498.85	52992.55	1591.88	3484.51	7779.21	50330.73	27695.98	26354.48	71.98	69089.55
32	1000	25	0.25	2	0.01	15287.04	4817.62	41469.05	9401.63	1591.88	4167.51	18391.66	13887.23	13626.70	12708.21	71.87	41469.05

Appendix D1 – Table 12 Full factorial data set featuring fitness (RotChr on – Gene 11 locked in first location) (GA optimisation case study).

Run	POPSIZE	MAXGEN	XOVER	TOURN	MUTPRO	Seeds								Mean	STD	SNR	Peak
						0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958				
1	100	99	0.25	1	0.001	6047.35	6621.44	2813.65	3747.53	581.44	1718.99	6047.12	4715.56	4036.64	2207.66	63.45	6621.44
2	1000	25	0.25	1	0.001	16545.79	11546.20	3747.53	49879.00	1590.16	2849.00	19094.23	49019.19	19283.89	19683.95	71.22	49879.00
3	1000	25	0.25	2	0.001	18470.27	15583.61	3747.53	8991.39	1590.16	5100.86	14020.61	49019.19	14565.45	15164.22	71.79	49019.19
4	1000	25	0.25	1	0.01	49338.67	9010.42	3747.53	7667.73	1590.16	2849.00	19094.23	49019.19	17789.62	20123.49	71.09	49338.67
5	1000	99	0.9	1	0.001	19147.18	49484.07	3747.53	11487.82	1590.16	5100.86	51203.49	72684.11	26805.65	27114.26	71.90	72684.11
6	100	25	0.25	1	0.01	2618.10	4637.32	2813.65	3004.70	581.44	1718.99	2836.53	4715.56	2865.79	1372.05	63.13	4715.56
7	100	25	0.25	2	0.001	925.51	8961.51	2813.65	1684.45	286.86	1535.65	8519.60	4715.56	3680.35	3397.90	57.48	8961.51
8	100	25	0.9	1	0.01	6047.35	2126.19	705.55	3438.52	581.44	1609.79	5023.02	1988.10	2689.99	1986.98	61.27	6047.35
9	1000	99	0.9	1	0.01	39710.91	49484.07	3747.53	49477.48	1590.16	5100.86	51203.49	49879.00	31274.19	23303.45	71.98	51203.49
10	100	99	0.25	1	0.01	6047.35	8854.61	2813.65	5291.19	581.44	1718.99	6047.12	4715.56	4508.74	2682.09	63.50	8854.61
11	100	25	0.9	1	0.001	4423.42	1965.52	705.55	4164.85	581.44	1609.79	5023.02	2082.41	2569.50	1730.06	61.26	5023.02
12	1000	25	0.9	2	0.001	7988.60	9462.19	6295.49	4477.92	1590.16	3905.18	15522.25	5627.95	6858.72	4261.00	71.26	15522.25
13	100	99	0.9	1	0.001	4423.42	4422.28	705.55	18679.51	581.44	1609.79	5023.02	9506.38	5618.93	6029.67	61.62	18679.51
14	100	99	0.25	2	0.001	5502.48	8961.51	2813.65	15297.34	286.86	1718.99	8519.60	4715.56	5977.00	4848.75	57.98	15297.34
15	100	25	0.25	1	0.001	6047.35	6621.44	2813.65	3747.53	581.44	1718.99	2836.53	4715.56	3635.31	2077.98	63.33	6621.44
16	1000	25	0.9	1	0.001	7225.08	8953.91	3747.53	9859.20	1590.16	5100.86	9323.80	49879.00	11959.94	15596.22	71.56	49879.00
17	100	25	0.9	2	0.001	3553.95	8961.51	782.81	1676.42	286.86	1774.87	10053.25	4167.39	3907.13	3701.44	57.38	10053.25
18	1000	99	0.25	2	0.01	50647.17	49879.00	6680.05	18157.83	1590.16	5100.86	14020.61	50919.03	24624.34	22020.73	72.35	50919.03
19	100	99	0.25	2	0.01	6944.19	6621.44	2813.65	15297.34	286.86	1718.99	8519.60	5673.78	5984.48	4710.03	57.99	15297.34
20	1000	99	0.25	2	0.001	49338.67	15583.61	6680.05	50919.03	1590.16	5100.86	14020.61	49879.00	24139.00	21928.56	72.34	50919.03
21	100	99	0.9	2	0.001	6125.26	8961.51	782.81	6621.44	286.86	1774.87	10053.25	26050.89	7582.11	8326.60	57.52	26050.89
22	100	99	0.9	2	0.01	5728.38	8406.98	782.81	3911.61	286.86	1774.87	10053.25	26050.89	7124.46	8420.14	57.50	26050.89
23	100	99	0.9	1	0.01	6047.35	2881.89	705.55	12680.43	581.44	1609.79	5023.02	26050.89	6947.55	8675.33	61.59	26050.89
24	100	25	0.9	2	0.01	2620.14	1602.49	782.81	2288.83	286.86	1774.87	10053.25	2949.26	2794.82	3065.83	57.28	10053.25
25	1000	25	0.9	1	0.01	7225.08	6614.66	3747.53	6084.90	1590.16	5100.86	9323.80	13397.29	6635.54	3580.72	71.31	13397.29
26	1000	99	0.25	1	0.001	25966.67	11546.20	6295.49	49879.00	1590.16	2849.00	48624.36	49879.00	24578.74	21925.54	71.59	49879.00
27	1000	99	0.9	2	0.01	18568.35	11419.55	10251.87	49879.00	1590.16	5100.86	35981.42	49477.48	22783.59	19591.18	72.45	49879.00
28	1000	25	0.9	2	0.01	18568.35	6960.96	6295.49	6581.74	1590.16	3905.18	15522.25	7769.24	8399.17	5743.35	71.60	18568.35
29	100	25	0.25	2	0.01	2533.77	4373.11	2813.65	2343.80	286.86	1535.65	8519.60	3404.57	3226.38	2458.03	57.83	8519.60
30	1000	99	0.9	2	0.001	36390.19	10936.01	10251.87	24392.18	1590.16	5100.86	35981.42	11461.72	17013.05	13538.05	72.38	36390.19
31	1000	99	0.25	1	0.01	49338.67	36390.19	6295.49	13488.47	1590.16	2849.00	48624.36	49019.19	25949.44	21944.70	71.62	49338.67
32	1000	25	0.25	2	0.01	16598.29	8423.50	3747.53	5160.73	1590.16	5100.86	14020.61	6582.42	7653.01	5169.14	71.33	16598.29

Appendix D1 – Table 13 Full factorial data set featuring fitness (RotChr on – Gene 12 locked in first location) (GA optimisation case study).

APPENDIX D2
TAGUCHI L_{16} DATA SETS FEATURING *FITNESS* (GA OPTIMISATION CASE STUDY)

Abbreviations

Run – run number.
FF Equiv. – Equivalent run in the full factorial array (Appendix D1).

Factors:
POPSIZE - Population Size
MAXGEN – Number of generations.
XOVER – Crossover probability.
MUTPRO – Mutation probability.
TOURN – Tournament size/winners.

Replications:
Seeds – Seeds required for random number generation. Each value (0.0251, 0.152, 0.253, 0.4174, 0.54, 0.756, 0.8757, 0.958) represents a replication.

Responses (Stats calculated for each run only):
Mean – Mean.
STD – Standard Deviation.
SNR – Signal-to-Noise Ratio.
Peak Value – maximum value amongst the eight replications of each run

Notes:
- **A*B** represents the interaction between factors **A** and **B**.

																	Seeds											
RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	6058.80	3926.00	2214.35	2843.70	526.30	5195.50	3219.80	7214.20	3899.83	2175.35	62.82	7214.20
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	6058.80	3926.00	2214.35	1062.10	526.30	5195.50	3219.80	7214.20	3677.13	2380.44	62.09	7214.20
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	5602.60	2595.40	2214.35	50582.30	442.95	2246.30	4311.00	3472.10	8933.38	16899.02	61.38	50582.30
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	5602.60	4707.40	2214.35	2473.30	526.30	2246.30	4000.80	4767.90	3317.37	1715.14	62.64	5602.60
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	6058.80	5633.10	2214.35	15177.30	526.30	5195.50	3219.80	7214.20	5654.92	4432.86	62.98	15177.30
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	7634.50	4603.00	2214.35	14921.30	526.30	2826.50	13386.20	4024.40	6267.07	5297.77	62.93	14921.30
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	6675.20	29494.10	2214.35	15260.80	442.95	3554.60	4165.60	4126.70	8241.79	9681.00	61.61	29494.10
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	9002.80	10920.00	2214.35	50582.30	526.30	4093.40	72987.90	5639.10	19495.77	26989.83	63.09	72987.90
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	51192.30	8537.00	2741.63	7707.60	1590.36	6705.70	18708.60	48151.00	18166.77	20128.97	71.36	51192.30
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	50312.50	18950.70	4501.38	50615.20	1590.36	11450.50	11270.40	7980.90	19583.99	19743.84	72.22	50615.20
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	13534.30	5424.30	2788.22	8296.50	1590.36	10178.70	6604.10	8482.20	7112.34	3895.44	71.08	13534.30
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	6314.20	18370.90	3554.24	5459.80	1590.36	18357.90	15602.50	5783.00	9379.11	6891.84	71.45	18370.90
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	24826.50	11731.50	2788.22	51962.50	1590.36	18750.90	15581.00	36547.00	20472.25	17077.69	71.70	51962.50
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	51204.10	11414.10	4501.38	25681.40	1590.36	49086.10	37172.40	24526.30	25647.02	19142.64	72.43	51204.10
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	36740.80	50262.50	2788.22	51962.50	1590.36	7686.70	50740.70	71657.50	34178.66	26751.94	71.68	71657.50
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	24985.50	11733.20	3554.24	19119.00	1590.36	12678.00	26270.60	35917.90	16981.10	11812.53	72.09	35917.90

Appendix D2 - Table 1 Taguchi L_{16} data set featuring fitness (RotChr off) (GA optimisation case study).

																	Seeds											
RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	5486.09	5428.44	725.08	1800.11	526.06	1536.53	6005.60	3737.54	3155.68	2278.43	60.96	6005.60
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	1716.69	3302.69	1846.50	6330.83	526.06	1536.53	3114.64	6526.17	3112.52	2228.75	62.12	6526.17
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	2471.96	3302.69	1365.68	6335.88	443.01	1536.53	6005.60	25740.48	5900.23	8295.63	60.99	25740.48
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	2471.81	2471.81	2471.81	2471.81	2471.81	2471.81	2471.81	2471.81	2471.81	0.00	67.86	2471.81
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	4426.22	5428.44	725.08	5561.80	526.06	1536.53	6005.60	4151.54	3545.16	2265.07	61.15	6005.60
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	6558.95	6558.95	6558.95	6558.95	6558.95	6558.95	6558.95	6558.95	6558.95	0.00	76.34	6558.95
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	11872.50	6603.32	5915.91	14884.99	1593.36	3323.04	6005.60	38131.91	11041.33	11768.75	71.43	38131.91
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	38131.91	0.00	91.63	38131.91
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	8910.79	8910.79	8910.79	8910.79	8910.79	8910.79	8910.79	8910.79	8910.79	0.00	79.00	8910.79
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	18601.34	18601.34	18601.34	18601.34	18601.34	18601.34	18601.34	18601.34	18601.34	0.00	85.39	18601.34
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	50440.34	50440.34	50440.34	50440.34	50440.34	50440.34	50440.34	50440.34	50440.34	0.00	94.06	50440.34
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	26447.95	8729.86	5202.03	42256.77	1593.36	2620.91	15532.98	19199.69	15197.94	13938.07	71.26	42256.77
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48

Appendix D2 - Table 2 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 1 locked in first location) (GA optimisation case study).

																Seeds											
RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	4414.03	3913.23	2097.13	3327.12	2706.40	1535.89	3323.57	26019.46	5917.10	8175.83	68.67	26019.46
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	2531.06	8937.79	1394.69	2538.45	2706.40	1535.89	6026.85	2964.00	3579.39	2590.50	67.16	8937.79
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	2409.55	7257.06	1714.45	2932.69	751.90	1649.06	6342.21	2964.00	3252.62	2319.74	64.37	7257.06
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	2345.38	4125.48	1254.94	3736.95	286.88	923.44	2373.21	18929.21	4246.94	6078.66	57.43	18929.21
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	5630.67	2767.66	2593.76	4029.12	286.88	1128.91	6101.74	4711.29	3406.25	2080.16	57.77	6101.74
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	3559.70	29878.40	2593.76	51962.54	286.88	923.44	8902.29	26107.41	15526.80	18690.54	57.71	51962.54
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	9523.31	6539.47	1254.94	15353.98	286.88	1104.78	2780.41	5659.30	5312.88	5155.09	57.63	15353.98
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	2883.72	3650.68	1254.94	4878.54	286.88	4947.60	5025.23	6197.59	3640.65	2042.68	57.85	6197.59
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	69193.01	6604.98	6596.60	6617.37	1728.50	7575.21	24577.83	7764.70	16332.27	22390.65	72.60	69193.01
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	5807.19	40080.72	9393.40	9647.96	1728.50	6771.66	5020.27	49909.80	16044.94	18232.71	72.51	49909.80
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	11726.67	8983.17	9393.40	9821.00	2139.03	6771.66	25793.79	7755.46	10298.02	6870.26	74.26	25793.79
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	4131.67	7240.57	9393.40	37079.19	1728.50	4628.36	4284.74	4940.42	9178.36	11500.54	71.50	37079.19
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	18360.59	71106.00	9393.40	26214.81	1728.50	6771.66	15396.41	49909.80	24860.15	23908.43	73.27	71106.00
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	51862.38	50743.42	9393.40	51962.54	1728.50	6771.66	9470.42	49324.57	28907.11	23722.86	73.23	51962.54
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	26447.95	8729.86	5202.03	42256.77	1593.36	2620.91	15532.98	19199.69	15197.94	13938.07	71.26	42256.77
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	25740.48	0.00	88.21	25740.48

Appendix D2 - Table 3 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 2 locked in first location) (GA optimisation case study).

																	Seeds										
RUN	**EQUIV. FF RUN**	**POPSIZE**	**MAXGEN**	**POPSIZE*MAXGE**	**XOVER**	**POPSIZE*XOVER**	**MAXGEN*XOVER**	**TOURN*MUTPRO**	**TOURN**	**POPSIZE*TOURN**	**MAXGEN*TOURN**	**XOVER*MUTPRO**	**XOVER*TOURN**	**MAXGE*MUTPRO**	**POPSIZE*MUTPRO**	**MUTPRO**	**0.0251**	**0.152**	**0.253**	**0.4174**	**0.54**	**0.756**	**0.8757**	**0.958**	**MEAN**	**STD**	**LTB**	**PEAK**
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	6702.64	7163.47	2214.09	2457.05	581.29	1068.84	5207.09	1873.81	3408.54	2572.95	62.43	7163.47
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	2698.75	1180.36	2214.09	2843.31	263.75	1393.78	4812.32	2949.26	2294.45	1384.39	56.93	4812.32
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	6702.64	3948.83	2214.09	3479.43	581.29	622.39	6049.05	5605.06	3650.35	2380.28	61.27	6702.64
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	3555.44	7163.47	2214.09	4174.63	329.69	1393.78	6049.05	1556.72	3304.61	2390.11	58.81	7163.47
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	5443.32	4760.94	2214.09	11860.80	581.29	1068.84	5207.09	4405.81	4442.77	3545.15	62.79	11860.80
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	3305.19	3643.18	2214.09	5904.46	263.75	1393.78	4812.32	3665.56	3150.29	1819.50	57.15	5904.46
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	3560.92	6669.61	2214.09	52354.09	581.29	622.39	12740.67	7635.84	10797.36	17286.28	61.34	52354.09
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	8458.78	11347.18	2214.09	6354.73	329.69	1393.78	6346.04	4405.81	5106.26	3755.71	59.01	11347.18
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	6672.33	7980.40	30102.66	8032.00	1593.38	6400.06	6894.20	5492.76	9145.97	8708.77	71.81	30102.66
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	3074.30	3163.88	30102.66	11831.36	1593.38	2602.12	3747.97	5898.76	7751.80	9584.52	69.71	30102.66
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	13574.19	8678.70	30102.66	7185.13	1593.38	6400.06	6560.33	8728.36	10352.85	8640.80	72.10	30102.66
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	4158.38	16395.06	4536.26	5572.39	1593.38	6400.06	6560.33	6902.97	6514.85	4348.42	71.21	16395.06
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	11001.97	51345.75	30102.66	37354.16	1593.38	6400.06	50696.32	49441.07	29741.92	20840.60	72.70	51345.75
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	18522.89	24498.12	30102.66	10795.17	1593.38	4830.11	49910.77	49486.93	23717.50	18638.33	72.48	49910.77
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	13434.96	8976.70	30102.66	52354.09	1593.38	6400.06	13434.96	76173.19	25308.75	26214.20	72.56	76173.19
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	24928.71	37354.05	4536.26	11112.07	1593.38	6400.06	50223.41	50223.41	23296.42	20379.67	72.24	50223.41

Appendix D2 - Table 4 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 3 locked in first location) (GA optimisation case study).

																	Seeds											
RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	15400.14	7565.97	1036.44	51771.31	421.21	1536.04	6035.30	5419.15	11148.20	17112.32	60.53	51771.31
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	2894.24	2589.64	3404.87	1436.64	438.02	1903.63	6035.30	2086.76	2598.64	1660.97	60.85	6035.30
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	2222.40	2480.80	1912.75	2844.37	421.21	1536.04	8890.19	1984.59	2786.54	2570.01	60.53	8890.19
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	2222.40	2364.03	3404.87	2844.37	438.02	1536.04	6035.30	5175.25	3002.54	1845.80	61.04	6035.30
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	7763.86	18684.14	1036.44	21000.40	421.21	1536.04	6035.30	7632.50	8013.74	7882.37	60.54	21000.40
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	4503.85	4598.92	3404.87	8279.76	438.02	1903.63	6035.30	6007.37	4396.47	2486.54	61.44	8279.76
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	8958.48	6117.96	1912.75	5650.31	421.21	1536.04	8890.19	4152.82	4704.97	3273.11	60.92	8958.48
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	2617.12	9670.54	3404.87	8279.76	438.02	1536.04	6035.30	24880.65	7107.79	7877.40	61.31	24880.65
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	18289.68	15431.54	3746.40	12633.41	1593.45	2855.52	14806.91	6669.29	9503.27	6526.89	71.05	18289.68
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	30416.43	18601.23	3746.40	8559.18	1593.45	2311.96	6386.34	12768.70	10547.96	9856.79	70.58	30416.43
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	36951.37	49033.92	3746.40	36937.35	1593.45	3027.00	11428.36	49965.30	24085.39	21200.15	71.37	49965.30
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	18673.20	11308.42	3746.40	6583.97	1593.45	2311.96	6035.30	7911.92	7270.58	5580.20	70.40	18673.20
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	72749.98	15039.32	3746.40	15259.58	1593.45	2855.52	18289.68	36685.50	20777.43	23913.69	71.25	72749.98
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	12672.70	50244.71	3746.40	9256.17	1593.45	3494.92	50244.71	50244.71	22687.22	23086.72	71.50	50244.71
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	9882.73	50244.71	3746.40	51617.11	1593.45	3027.00	11428.36	7703.71	17405.43	20971.49	71.18	51617.11
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	49162.28	24880.65	4172.34	25758.23	1593.45	3494.92	50950.31	50244.71	26282.11	21798.08	71.73	50950.31

Appendix D2 - Table 5 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 4 locked in first location) (GA optimisation case study).

																	Seeds											
RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	2840.83	36251.76	971.41	7491.27	255.46	1590.86	4605.97	4984.40	7373.99	11910.21	56.72	36251.76
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	4396.05	4529.74	1446.09	1438.49	329.78	1590.86	1212.13	2961.79	2238.11	1549.74	58.44	4529.74
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	2528.31	5461.15	950.54	2818.63	255.46	1590.86	2366.68	4713.71	2585.67	1772.63	56.63	5461.15
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	2695.33	1579.32	1446.09	3714.00	329.78	791.73	2831.01	1647.44	1879.34	1124.60	58.11	3714.00
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	25951.12	4464.52	1446.09	10878.25	255.46	1590.86	4605.97	4499.57	6711.48	8430.60	56.89	25951.12
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	25951.12	7171.57	1446.09	4017.28	329.78	1590.86	3300.53	3662.80	5933.75	8352.89	58.90	25951.12
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	6062.93	6732.62	1446.09	4017.28	255.46	1590.86	4464.52	4410.54	3622.54	2308.85	56.88	6732.62
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	6062.93	11691.86	1446.09	11666.90	329.78	1026.11	4514.47	23973.24	7588.92	7992.77	58.73	23973.24
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	13563.21	24092.50	6617.10	51595.23	1590.03	7331.27	49735.73	51056.83	25697.74	21791.19	72.54	51595.23
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	4776.71	28995.10	6617.10	6613.74	1590.03	6375.27	6932.13	6398.14	8537.28	8452.74	71.58	28995.10
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	36326.86	12650.96	6617.10	49029.11	1590.03	4259.21	7181.19	51056.83	21088.91	20868.39	72.04	51056.83
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	18192.75	2710.92	6617.10	5433.29	1590.03	6375.27	10111.93	51056.83	12761.02	16305.60	71.06	51056.83
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	24126.41	18209.42	6617.10	52154.35	1590.03	9797.36	49735.73	51056.83	26660.90	21280.63	72.65	52154.35
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	50193.05	12912.79	6617.10	12576.47	1590.03	6375.27	14764.77	36765.84	17724.42	16851.01	72.39	50193.05
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	29115.78	10843.85	12705.69	11310.08	1590.03	4259.21	41270.06	49644.69	20092.42	17782.45	72.26	49644.69
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	35616.87	49744.95	6617.10	26451.49	1590.03	6375.27	10111.93	24126.41	20079.26	16855.20	72.43	49744.95

Appendix D2 - Table 6 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 5 locked in first location) (GA optimisation case study).

																	Seeds											
RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	6042.62	15362.16	2249.41	2603.42	255.42	979.53	2808.26	5183.68	4435.56	4821.60	56.75	15362.16
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	2349.73	1830.96	2249.41	6655.75	255.42	1587.26	3288.44	4601.60	2852.32	1989.97	56.84	6655.75
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	1463.99	7130.87	2249.41	4495.41	255.42	1587.26	1933.39	4081.64	2899.67	2203.20	56.78	7130.87
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	2100.77	1068.03	2249.41	3569.72	255.42	1078.76	2808.26	1608.99	1842.42	1062.66	56.46	3569.72
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	6042.62	5897.80	2249.41	5638.60	255.42	1587.26	3273.73	4693.45	3704.79	2193.43	56.95	6042.62
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	3869.37	7169.34	2249.41	6641.33	255.42	1587.26	4015.28	4693.45	3810.11	2394.60	56.95	7169.34
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	67663.77	7130.87	2249.41	15260.82	255.42	1587.26	2957.79	4601.60	12713.37	22698.83	56.96	67663.77
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	6042.62	7278.42	2249.41	8576.75	255.42	1424.29	10807.42	4245.75	5110.01	3705.83	56.95	10807.42
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	26546.09	7200.31	9500.65	67043.14	1589.37	20788.70	19116.33	8980.85	20095.68	20673.24	72.54	67043.14
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	8385.03	15296.49	9500.65	51398.92	1589.37	67043.14	8058.68	11698.82	21621.39	23891.54	72.51	67043.14
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	15012.25	5872.08	9500.65	11101.42	1589.37	20788.70	15296.49	11551.84	11339.10	5938.68	72.38	20788.70
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	4687.53	5082.53	9500.65	4315.51	1589.37	2352.57	7645.99	4129.68	4912.98	2595.83	69.99	9500.65
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	9398.25	18219.72	9500.65	47608.38	1589.37	20788.70	19116.33	8994.94	16902.04	14003.63	72.60	47608.38
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	18305.02	10794.07	9500.65	11648.86	1589.37	67043.14	52878.11	50574.51	27791.72	24927.59	72.73	67043.14
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	50554.79	49653.29	9500.65	51398.92	1589.37	20788.70	15296.49	37227.37	29501.20	20161.27	72.85	51398.92
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	18212.58	29065.98	9500.65	52878.11	1589.37	2352.57	15527.88	37687.07	20851.78	17944.38	71.27	52878.11

Appendix D2 - Table 7 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 6 locked in first location) (GA optimisation case study).

RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	Seeds 0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	4615.95	2552.72	2093.04	2115.47	378.19	938.78	2806.20	2510.28	2251.33	1272.35	59.46	4615.95
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	1168.12	5226.05	1130.00	5448.06	378.19	1692.18	1142.89	2261.39	2305.86	1946.61	59.08	5448.06
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	6066.53	6335.75	1130.00	3292.80	378.19	1692.18	3005.16	2467.63	3046.03	2170.06	59.71	6335.75
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	6066.53	2595.96	2597.88	2563.44	378.19	740.43	2371.51	6406.77	2965.09	2200.33	59.26	6406.77
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	6066.53	4696.77	2093.04	3394.26	378.19	938.78	3477.78	5658.73	3338.01	2096.47	59.67	6066.53
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	5902.37	2197.84	1130.00	6548.15	378.19	4905.31	2371.51	10161.83	4199.40	3291.46	59.86	10161.83
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	4615.95	51082.16	2093.04	3150.43	378.19	1692.18	3368.11	3942.67	8790.34	17141.16	60.07	51082.16
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	6382.49	2957.84	2597.88	7955.48	378.19	1521.90	2388.86	5008.90	3648.94	2570.72	60.03	7955.48
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	70853.73	7385.80	2935.81	8584.54	1591.51	5630.44	4804.27	8989.90	13847.00	23180.45	71.04	70853.73
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	7006.06	5188.05	8916.84	7734.87	1591.51	4905.31	9473.49	10846.52	6957.83	2976.97	71.68	10846.52
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	4591.23	10185.49	4600.79	8518.52	1591.51	2408.70	50479.01	26192.95	13571.03	16851.07	70.66	50479.01
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	6111.57	3938.44	4600.79	7734.87	1591.51	2958.72	2371.51	18593.03	5987.56	5472.83	69.76	18593.03
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	11663.75	18246.62	3553.33	11617.50	1591.51	5630.44	51828.08	51082.16	19401.68	20476.28	71.84	51828.08
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	16511.23	37567.24	8916.84	15278.78	1591.51	4905.31	13455.91	51082.16	18663.62	17017.92	72.37	51082.16
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	18552.67	51180.94	4600.79	25917.03	1591.51	2408.70	50479.01	51082.16	25726.60	22448.47	71.11	51180.94
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	15250.38	11382.56	4600.79	52145.71	1591.51	4905.31	51828.08	26192.95	20987.16	20624.56	72.06	52145.71

Appendix D2 - Table 8 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 7 locked in first location) (GA optimisation case study).

RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	Seeds 0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	5602.93	3114.71	804.72	10536.49	437.25	1589.47	8927.36	2547.50	4195.05	3796.18	60.29	10536.49
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	2603.37	6340.76	2019.18	1251.55	437.25	1589.47	6049.57	6439.86	3341.38	2509.83	60.75	6439.86
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	3926.97	5087.43	804.72	3563.57	437.25	1589.47	6049.57	25632.78	5886.47	8227.13	60.35	25632.78
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	1891.35	5816.92	2591.27	3450.82	389.43	1589.47	6049.57	1392.07	2896.36	2074.97	59.96	6049.57
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	5304.37	18238.23	804.72	12754.44	437.25	1840.80	8927.36	3600.37	6488.44	6364.34	60.46	18238.23
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	5610.37	5090.69	2019.18	5907.38	437.25	71108.99	6049.57	35786.26	16501.21	24761.66	61.55	71108.99
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	7991.94	5879.64	804.72	50503.12	437.25	1589.47	6049.57	25632.78	12361.06	17417.73	60.43	50503.12
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	5481.35	5683.62	2591.27	5550.21	389.43	1589.47	37553.60	9475.31	8539.28	12066.75	60.43	37553.60
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	12590.86	10195.38	4586.42	8927.36	3920.65	71108.99	6702.74	25632.78	17958.15	22542.26	76.85	71108.99
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	6117.44	6619.68	6671.86	10846.74	3920.65	71108.99	5112.72	51382.91	20222.62	25939.43	76.37	71108.99
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	8031.09	6338.29	4586.42	51295.29	3920.65	71108.99	40250.16	8990.28	24315.14	26185.78	76.82	71108.99
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	5511.62	15248.47	4586.42	12704.94	3920.65	71108.99	8902.10	15464.24	17180.93	22277.86	76.65	71108.99
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	71108.99	18829.17	4586.42	49065.42	3920.65	71108.99	13399.52	51382.91	35425.26	28514.40	78.16	71108.99
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	48546.99	18207.71	6671.86	37754.84	3920.65	71108.99	48325.91	51382.91	35739.98	23865.57	79.36	71108.99
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	35915.24	12555.18	4586.42	38014.98	3920.65	71108.99	40250.16	38014.98	30545.82	22635.01	78.17	71108.99
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	18544.52	15340.62	4586.42	50552.73	3920.65	71108.99	10063.64	69363.36	30435.12	28610.41	77.88	71108.99

Appendix D2 - Table 9 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 8 locked in first location) (GA optimisation case study).

																	Seeds											
RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	3313.91	4614.48	1422.99	4510.03	336.77	4952.11	3322.18	3451.43	3240.49	1613.37	59.16	4952.11
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	4405.38	1631.81	710.01	3284.13	702.36	4952.11	1088.76	2486.29	2407.61	1663.52	61.57	4952.11
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	6051.55	10077.60	895.11	3000.95	802.02	992.01	1198.69	3042.85	3257.60	3282.28	62.24	10077.60
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	6051.55	8673.95	879.30	2160.42	702.36	1206.38	5796.92	9410.31	4360.15	3572.09	62.69	9410.31
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	4405.38	6090.82	1422.99	7820.92	336.77	4952.11	6001.50	4765.28	4474.47	2475.38	59.25	7820.92
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	9544.00	3771.45	895.11	4365.12	702.36	53714.52	19037.55	25839.96	14733.76	18143.76	63.70	53714.52
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	7136.97	5444.68	895.11	4259.48	802.02	4952.11	6425.65	7799.55	4714.45	2645.91	64.27	7799.55
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	6051.55	8673.95	895.11	3319.61	702.36	1206.38	6001.50	3452.07	3787.82	2897.85	62.79	8673.95
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	5693.25	41990.96	9383.12	51587.57	1592.90	2595.38	8212.86	4327.10	15672.89	19549.59	70.88	51587.57
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	19229.57	9746.02	9383.12	52624.43	1592.90	53714.52	51523.00	24212.31	27753.23	21675.67	72.78	53714.52
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	26126.38	16183.38	9383.12	6740.26	1592.90	2595.38	6001.50	25839.96	11807.86	9823.83	71.17	26126.38
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	10116.21	68047.59	9383.12	15092.76	1592.90	4952.11	8897.77	3829.12	15238.95	21750.98	71.70	68047.59
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	19037.55	26126.38	9383.12	50615.16	1592.90	2595.38	51880.88	24212.31	23180.46	19579.21	71.54	51880.88
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	48874.57	68047.59	9383.12	24183.42	1592.90	53714.52	51880.88	25839.96	35439.62	23578.02	72.90	68047.59
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	16319.64	48522.71	9383.12	51330.22	1592.90	2595.38	6646.53	25839.96	20278.81	19910.27	71.38	51330.22
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	18346.80	9317.90	9383.12	11941.81	1592.90	4952.11	16519.39	24183.42	12029.68	7379.13	72.28	24183.42

Appendix D2 - Table 10 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 9 locked in first location) (GA optimisation case study).

RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	Seeds								MEAN	STD	LTB	PEAK
																	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958				
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	4414.03	3913.23	2097.13	3327.12	2706.40	1535.89	3323.57	26019.46	5917.10	8175.83	68.67	26019.46
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	2531.06	8937.79	1394.69	2538.45	2706.40	1535.89	6026.85	2964.00	3579.39	2590.50	67.16	8937.79
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	2409.55	7257.06	1714.45	2932.69	751.90	1649.06	6342.21	2964.00	3252.62	2319.74	64.37	7257.06
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	8659.63	15166.37	1714.45	4517.26	2706.40	1649.06	2782.43	3488.36	5085.50	4650.80	68.53	15166.37
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	7031.95	6991.51	6418.16	12624.04	2706.40	1535.89	5888.72	4886.85	6010.44	3340.82	70.57	12624.04
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	7922.37	10097.67	1394.69	5057.68	2706.40	1535.89	6026.85	4504.67	4905.78	3071.01	68.18	10097.67
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	6051.17	4496.43	1714.45	3197.56	751.90	1649.06	8948.10	4885.93	3961.83	2716.49	64.71	8948.10
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	5611.79	8943.19	1714.45	7206.45	2706.40	1844.99	9522.50	3931.09	5185.11	3119.58	69.44	9522.50
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	69193.01	6604.98	6596.60	6617.37	2706.40	7575.21	24577.83	7764.70	16454.51	22302.03	75.21	69193.01
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	11360.94	6683.18	6460.18	8948.10	2706.40	2597.14	6073.28	14616.09	7430.66	4112.78	73.20	14616.09
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	8973.68	18284.08	6460.18	9829.64	2706.40	2600.57	6962.94	20936.48	9594.25	6736.89	73.50	20936.48
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	9000.87	5693.64	6596.60	37714.00	2706.40	2633.31	7601.50	11414.00	10420.04	11420.51	73.32	37714.00
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	74560.82	18284.08	6596.60	19113.21	2706.40	7575.21	24577.83	51225.59	25579.97	24958.86	76.36	74560.82
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	49058.75	8449.78	6460.18	42000.24	2706.40	4154.22	36711.30	50233.87	24971.84	21350.52	75.33	50233.87
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	14626.27	13626.61	6460.18	50031.57	2706.40	2600.57	18306.91	51225.59	19948.01	19764.36	73.95	51225.59
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	16637.96	49731.41	6596.60	9829.64	2706.40	2633.31	24708.44	51225.59	20508.67	19907.48	73.98	51225.59

Appendix D2 - Table 11 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 10 locked in first location) (GA optimisation case study).

RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	Seeds								MEAN	STD	LTB	PEAK
																	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958				
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	6059.20	2502.97	3806.85	3570.82	255.47	2682.41	2506.95	2961.50	3043.27	1623.29	56.97	6059.20
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	5514.20	19188.96	1136.94	2461.04	255.47	1744.21	5794.00	3647.85	4967.83	6077.15	56.80	19188.96
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	3002.85	3940.65	3806.85	6649.65	255.47	2682.41	6016.61	2588.59	3617.88	2024.99	57.02	6649.65
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	6721.62	4719.23	3806.85	2598.67	255.47	2682.41	2589.66	3784.78	3394.83	1881.82	57.00	6721.62
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	5514.20	10870.87	3806.85	7640.32	255.47	2682.41	36757.29	6117.08	9205.56	11583.78	57.10	36757.29
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	6059.20	4618.46	3806.85	8569.99	255.47	2319.39	9001.61	26855.46	7685.80	8290.25	57.08	26855.46
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	18205.67	5541.70	3806.85	52992.55	255.47	2682.41	6016.61	11658.26	12644.94	17258.86	57.10	52992.55
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	5541.70	3371.68	3806.85	9498.85	255.47	2818.88	5880.87	4674.66	4481.12	2688.70	57.07	9498.85
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	18574.21	8693.67	9498.85	15631.21	1591.88	3484.51	7153.29	7759.65	9048.41	5684.72	71.67	18574.21
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	15287.04	4817.62	41469.05	9401.63	1591.88	4167.51	18391.66	13887.23	13626.70	12708.21	71.87	41469.05
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	11762.42	50330.73	9498.85	10093.26	1591.88	4270.08	9567.61	26855.46	15496.28	15928.78	72.13	50330.73
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	11111.16	6664.42	9498.85	15149.87	1591.88	3484.51	9318.84	18458.05	9409.70	5625.15	71.73	18458.05
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	26800.59	69089.55	9498.85	52992.55	1591.88	3484.51	7779.21	50330.73	27695.98	26354.48	71.98	69089.55
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	50164.51	26480.55	41469.05	26480.55	1591.88	4167.51	37047.97	50330.73	29716.59	18896.82	72.43	50330.73
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	26800.59	26480.55	9498.85	52992.55	1591.88	4270.08	50348.50	15446.39	23428.67	19715.98	72.33	52992.55
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	50288.22	51954.48	9498.85	52992.55	1591.88	3484.51	10820.71	50330.73	28870.24	24271.18	72.06	52992.55

Appendix D2 - Table 12 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 11 locked in first location) (GA optimisation case study).

																	Seeds											
RUN	EQUIV. FF RUN	POPSIZE	MAXGEN	POPSIZE*MAXGE	XOVER	POPSIZE*XOVER	MAXGEN*XOVER	TOURN*MUTPRO	TOURN	POPSIZE*TOURN	MAXGEN*TOURN	XOVER*MUTPRO	XOVER*TOURN	MAXGE*MUTPRO	POPSIZE*MUTPRO	MUTPRO	0.0251	0.152	0.253	0.4174	0.54	0.756	0.8757	0.958	MEAN	STD	LTB	PEAK
1	6	100	25	1	0.25	1	1	1	1	1	1	1	1	1	1	0.01	2618.10	4637.32	2813.65	3004.70	581.44	1718.99	2836.53	4715.56	2865.79	1372.05	63.13	4715.56
2	7	100	25	1	0.25	1	1	1	2	2	2	2	2	2	2	0.001	925.51	8961.51	2813.65	1684.45	286.86	1535.65	8519.60	4715.56	3680.35	3397.90	57.48	8961.51
3	11	100	25	1	0.9	2	2	2	1	1	1	1	2	2	2	0.001	4423.42	1965.52	705.55	4164.85	581.44	1609.79	5023.02	2082.41	2569.50	1730.06	61.26	5023.02
4	24	100	25	1	0.9	2	2	2	2	2	2	2	1	1	1	0.01	2620.14	1602.49	782.81	2288.83	286.86	1774.87	10053.25	2949.26	2794.82	3065.83	57.28	10053.25
5	1	100	99	2	0.25	1	2	2	1	1	2	2	1	1	2	0.001	6047.35	6621.44	2813.65	3747.53	581.44	1718.99	6047.12	4715.56	4036.64	2207.66	63.45	6621.44
6	19	100	99	2	0.25	1	2	2	2	2	1	1	2	2	1	0.01	6944.19	6621.44	2813.65	15297.34	286.86	1718.99	8519.60	5673.78	5984.48	4710.03	57.99	15297.34
7	23	100	99	2	0.9	2	1	1	1	1	2	2	2	2	1	0.01	6047.35	2881.89	705.55	12680.43	581.44	1609.79	5023.02	26050.89	6947.55	8675.33	61.59	26050.89
8	21	100	99	2	0.9	2	1	1	2	2	1	1	1	1	2	0.001	6125.26	8961.51	782.81	6621.44	286.86	1774.87	10053.25	26050.89	7582.11	8326.60	57.52	26050.89
9	2	1000	25	2	0.25	2	1	2	1	2	1	2	1	2	1	0.001	16545.79	11546.20	3747.53	49879.00	1590.16	2849.00	19094.23	49019.19	19283.89	19683.95	71.22	49879.00
10	32	1000	25	2	0.25	2	1	2	2	1	2	1	2	1	2	0.01	16598.29	8423.50	3747.53	5160.73	1590.16	5100.86	14020.61	6582.42	7653.01	5169.14	71.33	16598.29
11	25	1000	25	2	0.9	1	2	1	1	2	1	2	2	1	2	0.01	7225.08	6614.66	3747.53	6084.90	1590.16	5100.86	9323.80	13397.29	6635.54	3580.72	71.31	13397.29
12	12	1000	25	2	0.9	1	2	1	2	1	2	1	1	2	1	0.001	7988.60	9462.19	6295.49	4477.92	1590.16	3905.18	15522.25	5627.95	6858.72	4261.00	71.26	15522.25
13	31	1000	99	1	0.25	2	2	1	1	2	2	1	1	2	2	0.01	49338.67	36390.19	6295.49	13488.47	1590.16	2849.00	48624.36	49019.19	25949.44	21944.70	71.62	49338.67
14	20	1000	99	1	0.25	2	2	1	2	1	1	2	2	1	1	0.001	49338.67	15583.61	6680.05	50919.03	1590.16	5100.86	14020.61	49879.00	24139.00	21928.56	72.34	50919.03
15	5	1000	99	1	0.9	1	1	2	1	2	2	1	2	1	1	0.001	19147.18	49484.07	3747.53	11487.82	1590.16	5100.86	51203.49	72684.11	26805.65	27114.26	71.90	72684.11
16	27	1000	99	1	0.9	1	1	2	2	1	1	2	1	2	2	0.01	18568.35	11419.55	10251.87	49879.00	1590.16	5100.86	35981.42	49477.48	22783.59	19591.18	72.45	49879.00

Appendix D2 - Table 13 Taguchi L_{16} data set featuring fitness (RotChr on – Gene 12 locked in first location) (GA optimisation case study).

APPENDIX D3
SUMMARY OF ANALYSES FOR THE FULL FACTORIAL DATA SETS FEATURING *FITNESS* (GA OPTIMISATION CASE STUDY)

Abbreviations

Run – run number.

Factors:
POPSIZE - Population Size
MAXGEN – Number of generations.
XOVER – Crossover probability.
MUTPRO – Mutation probability.
TOURN – Tournament size/winners.

Results
F – F-Value
P – Probability of rejecting the hypothesis

Responses (Stats calculated for each run only):
Mean – Mean.
STD – Standard Deviation.
Smaller-the-Better – Signal-to-Noise Ratio.
Peak Value – maximum value amongst the eight replications of each run.

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	94.19	0	17.37	0.001	5533.92	0	18.11	0.001
		MAXGEN	51.72	0	14.63	0.001	13.66	0.002	16.46	0.001
		XOVER	0.1	0.759	0.06	0.812	15.33	0.001	0.13	0.725
		TOURN	2.44	0.137	1.5	0.238	13.44	0.002	2.7	0.12
		MUTPRO	15.85	0.001	10.19	0.006	0.06	0.81	9.2	0.008
	Interactions	POPSIZE*MAXGEN	12.78	0.003	1.49	0.24	0.04	0.84	0.97	0.339
		POPSIZE*XOVER	7.63	0.014	7.22	0.016	1.63	0.22	8.17	0.011
		POPSIZE*TOURN	0.12	0.734	0.05	0.83	0	0.957	0.04	0.84
		POPSIZE*MUTPRO	0.82	0.377	0.09	0.766	0.32	0.58	0.28	0.606
		MAXGEN*XOVER	3.74	0.071	2.48	0.135	0.4	0.534	1.72	0.208
		MAXGEN*TOURN	0	0.962	0.11	0.742	1.24	0.281	0	0.983
		MAXGEN*MUTPRO	5.89	0.027	1.24	0.281	0.34	0.567	0.99	0.334
		XOVER*TOURN	0.03	0.872	0.01	0.911	5.32	0.035	0.1	0.759
		XOVER*MUTPRO	7.54	0.014	6.13	0.025	0.66	0.427	6.11	0.025
		TOURN*MUTPRO	4.79	0.044	3.18	0.093	0.3	0.593	3.3	0.088
		Error	1.69E+08		3.81E+08		1.999		2.51E+09	

Appendix D3 – Table 1 Summary of analysis: OOBF with RotChr off (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	6.29	0.023	2.07	0.17	6.58	0.021	16.54	0.001
		MAXGEN	9.5	0.007	0.03	0.873	7.09	0.017	10.95	0.004
		XOVER	2.64	0.124	0.02	0.898	2.21	0.156	3.99	0.063
		TOURN	1.31	0.27	5.16	0.037	3.26	0.09	0.18	0.68
		MUTPRO	0.32	0.581	0.14	0.712	0.07	0.795	1.12	0.305
	Interactions	POPSIZE*MAXGEN	0.1	0.758	0.21	0.653	0.5	0.491	0.43	0.52
		POPSIZE*XOVER	1.62	0.221	0.03	0.87	2.76	0.116	2.4	0.141
		POPSIZE*TOURN	0.05	0.826	1.16	0.297	0.2	0.66	0.33	0.571
		POPSIZE*MUTPRO	0.83	0.375	0	0.979	0.01	0.935	1.24	0.281
		MAXGEN*XOVER	1.09	0.311	3.12	0.096	0.13	0.727	6.52	0.021
		MAXGEN*TOURN	3.11	0.097	0.27	0.609	1.31	0.27	3.12	0.096
		MAXGEN*MUTPRO	0.96	0.342	0.64	0.434	0.07	0.798	0.14	0.715
		XOVER*TOURN	0.06	0.807	0.66	0.428	0	0.985	0.13	0.726
		XOVER*MUTPRO	0.01	0.93	0.05	0.832	0.13	0.719	0.07	0.799
		TOURN*MUTPRO	0.3	0.59	0.09	0.762	0.01	0.917	0.56	0.464
		Error	3.38E+09		3.75E+08		1660.4		2.53E+09	

Appendix D3 – Table 2 Summary of analysis: OOBF with RotChr on (Gene 1 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	214.96	0	76.17	0	102.12	0	66.58	0
		MAXGEN	84.01	0	21.97	0	0.44	0.517	9.89	0.006
		XOVER	34.04	0	25.2	0	2.7	0.12	20.2	0
		TOURN	4.14	0.059	0.21	0.655	1.14	0.301	0.03	0.86
		MUTPRO	1.97	0.179	1.68	0.214	2.53	0.131	2.24	0.154
	Interactions	POPSIZE*MAXGEN	15.32	0.001	0.71	0.413	2.95	0.105	0.02	0.896
		POPSIZE*XOVER	0.73	0.406	0	0.96	1.27	0.276	0	0.955
		POPSIZE*TOURN	0.94	0.348	0.03	0.868	0.15	0.708	0.02	0.895
		POPSIZE*MUTPRO	5.88	0.028	4.93	0.041	1.39	0.256	4.6	0.048
		MAXGEN*XOVER	0.05	0.829	0.49	0.496	0.05	0.832	0.72	0.408
		MAXGEN*TOURN	3.92	0.065	0.97	0.339	0.02	0.882	0.82	0.379
		MAXGEN*MUTPRO	0.62	0.444	2.21	0.157	0.06	0.812	2.91	0.107
		XOVER*TOURN	0.08	0.78	0.01	0.921	2.32	0.147	0.14	0.714
		XOVER*MUTPRO	3.09	0.098	2.92	0.107	2.01	0.175	4.41	0.052
		TOURN*MUTPRO	20.75	0	10.2	0.006	3.39	0.084	8.7	0.009
		Error	81230955		198036907		190.28		1785149349	

Appendix D3 – Table 3 Summary of analysis: OOBF with RotChr on (Gene 2 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	149.38	0	73.16	0	232.86	0	52.09	0
		MAXGEN	69.71	0	33.78	0	1	0.332	20.09	0
		XOVER	2.25	0.153	0.32	0.58	0.03	0.869	0.27	0.608
		TOURN	0.6	0.449	0.38	0.545	0.2	0.657	0.17	0.69
		MUTPRO	2.63	0.124	1.24	0.283	0.27	0.612	0.47	0.503
	Interactions	POPSIZE*MAXGEN	41.36	0	17.82	0.001	1.06	0.319	8.9	0.009
		POPSIZE*XOVER	5.96	0.027	5.66	0.03	0	0.95	2.88	0.109
		POPSIZE*TOURN	0.1	0.76	0.63	0.441	0.01	0.922	0.85	0.37
		POPSIZE*MUTPRO	0.13	0.725	2.2	0.158	0.25	0.623	1.33	0.266
		MAXGEN*XOVER	0.07	0.791	0.63	0.439	0.01	0.938	0.45	0.513
		MAXGEN*TOURN	1.71	0.21	0.34	0.568	0.01	0.908	0.1	0.759
		MAXGEN*MUTPRO	0.02	0.899	0.2	0.664	0.02	0.895	0.07	0.79
		XOVER*TOURN	2.87	0.11	3.52	0.079	1.25	0.28	1.46	0.244
		XOVER*MUTPRO	2.12	0.164	0.19	0.67	0.1	0.75	0	0.977
		TOURN*MUTPRO	0.05	0.82	0.95	0.343	0.67	0.424	0.17	0.685
		Error	140021438		217636275		67.997		2421693979	

Appendix D3 – Table 4 Summary of analysis: OOBF with RotChr on (Gene 3 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	34.41	0	15.21	0.001	3765.04	0	11.33	0.004
		MAXGEN	18.68	0.001	9.92	0.006	9.44	0.007	6.59	0.021
		XOVER	0	0.957	0.03	0.866	0.13	0.723	0.06	0.808
		TOURN	0.39	0.539	0.83	0.377	0.71	0.413	0.92	0.353
		MUTPRO	2.08	0.169	1.57	0.228	0.02	0.898	1.89	0.188
	Interactions	POPSIZE*MAXGEN	5.21	0.036	2.5	0.133	1.02	0.326	1.15	0.3
		POPSIZE*XOVER	2.15	0.162	0.47	0.501	0.76	0.395	0.1	0.751
		POPSIZE*TOURN	0.26	0.615	0	0.961	0.01	0.913	0.13	0.72
		POPSIZE*MUTPRO	1.54	0.233	0.05	0.824	0.27	0.61	0.02	0.879
		MAXGEN*XOVER	0.52	0.48	0.38	0.548	0.39	0.54	0.27	0.609
		MAXGEN*TOURN	0.2	0.661	0.45	0.513	0.24	0.632	0.55	0.469
		MAXGEN*MUTPRO	1.13	0.304	1.26	0.279	0.06	0.805	2.13	0.164
		XOVER*TOURN	0.65	0.431	0.04	0.836	1.24	0.281	0.01	0.905
		XOVER*MUTPRO	0.1	0.759	0.33	0.574	0.02	0.887	1.04	0.323
		TOURN*MUTPRO	1.76	0.203	0.8	0.385	1.54	0.232	0.38	0.546
		Error	347664546		693421620		2.716		5492690047	

Appendix D3 – Table 5 Summary of analysis: OOBF with RotChr on (Gene 4 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	69.76	0	32.97	0	1706.07	0	34.44	0
		MAXGEN	15.48	0.001	8.66	0.01	1.78	0.201	9.44	0.007
		XOVER	5.91	0.027	4.1	0.06	0.33	0.571	2.13	0.164
		TOURN	0.36	0.558	0	0.985	0.33	0.576	0.09	0.77
		MUTPRO	0.09	0.765	0.02	0.885	0.1	0.761	0.05	0.831
	Interactions	POPSIZE*MAXGEN	1.66	0.215	0.08	0.78	0.06	0.815	0.05	0.825
		POPSIZE*XOVER	1.42	0.25	1.96	0.181	0.03	0.875	1.68	0.214
		POPSIZE*TOURN	0.54	0.472	0.17	0.686	0	0.962	0.02	0.898
		POPSIZE*MUTPRO	2.88	0.109	1.25	0.279	0.74	0.403	0.6	0.449
		MAXGEN*XOVER	0.01	0.913	0.05	0.835	0.11	0.748	0.08	0.786
		MAXGEN*TOURN	0.01	0.93	0.08	0.775	0.02	0.877	0.01	0.908
		MAXGEN*MUTPRO	2.91	0.108	1.85	0.193	0.1	0.758	1.65	0.217
		XOVER*TOURN	2.91	0.107	3.22	0.092	0.97	0.339	2.49	0.134
		XOVER*MUTPRO	0.32	0.582	0.98	0.336	0.19	0.671	2.75	0.117
		TOURN*MUTPRO	12.4	0.003	8.16	0.011	0.28	0.605	4.26	0.056
		Error	257082006		324962976		12.27		2219252978	

Appendix D3 – Table 6 Summary of analysis: OOBF with RotChr on (Gene 5 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	58.64	0	49.42	0	4392.52	0	61.76	0
		MAXGEN	12.14	0.003	11.1	0.004	2.72	0.118	10.6	0.005
		XOVER	1.73	0.207	1.07	0.316	7.12	0.017	1.05	0.321
		TOURN	2.55	0.13	5.31	0.035	0.04	0.848	6.01	0.026
		MUTPRO	0.19	0.669	0.02	0.88	0.06	0.812	0.13	0.723
	Interactions	POPSIZE*MAXGEN	3.27	0.089	0.5	0.49	0.26	0.617	0.12	0.732
		POPSIZE*XOVER	2.31	0.148	8.27	0.011	1.02	0.327	8.36	0.011
		POPSIZE*TOURN	0.28	0.605	0.02	0.898	0.08	0.781	0	0.97
		POPSIZE*MUTPRO	1.69	0.212	4.96	0.041	0.19	0.671	5.32	0.035
		MAXGEN*XOVER	0.2	0.662	1.3	0.271	0.2	0.658	2.05	0.172
		MAXGEN*TOURN	0.1	0.755	1.65	0.217	0.64	0.436	2.63	0.124
		MAXGEN*MUTPRO	0.28	0.601	0.09	0.772	0	0.988	0.95	0.343
		XOVER*TOURN	0.19	0.67	1.04	0.324	0	0.96	1.29	0.273
		XOVER*MUTPRO	0.53	0.476	4.38	0.053	0.03	0.864	5.9	0.027
		TOURN*MUTPRO	0	0.959	1.52	0.236	4.04	0.062	1.27	0.276
		Error	400137071		315664542		5.47		2218026297	

Appendix D3 – Table 7 Summary of analysis: OOBF with RotChr on (Gene 6 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	137.4	0	33.26	0	3970.8	0	27.64	0
		MAXGEN	59.99	0	15.69	0.001	17.18	0.001	9.17	0.008
		XOVER	1.25	0.28	0.34	0.566	1.48	0.242	0.08	0.785
		TOURN	0.38	0.546	3.06	0.1	0.06	0.81	5.03	0.039
		MUTPRO	0.5	0.488	0.38	0.545	0	0.97	0.62	0.443
	Interactions	POPSIZE*MAXGEN	25.22	0	3.55	0.078	3.1	0.098	0.93	0.348
		POPSIZE*XOVER	1.24	0.282	1.02	0.328	5.87	0.028	0.9	0.356
		POPSIZE*TOURN	0.16	0.695	0.16	0.698	0	0.956	0.05	0.822
		POPSIZE*MUTPRO	0.71	0.412	0.39	0.54	0.07	0.802	0.72	0.41
		MAXGEN*XOVER	0.66	0.429	0.19	0.666	0.45	0.512	0.04	0.842
		MAXGEN*TOURN	0.5	0.491	0.06	0.804	0	0.999	0.01	0.939
		MAXGEN*MUTPRO	0.46	0.509	1.42	0.251	0.06	0.813	1.21	0.288
		XOVER*TOURN	0.21	0.656	0.65	0.433	0.51	0.485	0.63	0.44
		XOVER*MUTPRO	0.79	0.388	3.23	0.091	0.01	0.905	3.84	0.068
		TOURN*MUTPRO	1	0.332	1.15	0.299	0.01	0.932	1.41	0.253
		Error	105293506		416285405		3.504		3314906111	

Appendix D3 – Table 8 Summary of analysis: OOBF with RotChr on (Gene 7 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	458.87	0	195.92	0	6736.34	0	211.4	0
		MAXGEN	101.57	0	20.92	0	20.15	0	25.09	0
		XOVER	3.56	0.077	0.32	0.577	4.38	0.053	0.29	0.599
		TOURN	1.18	0.294	2.55	0.13	0	0.978	1.57	0.228
		MUTPRO	7.4	0.015	8.44	0.01	0.91	0.354	3.73	0.072
	Interactions	POPSIZE*MAXGEN	9.15	0.008	13.03	0.002	3.55	0.078	19.37	0
		POPSIZE*XOVER	0.35	0.564	0.4	0.536	1.43	0.25	0.44	0.516
		POPSIZE*TOURN	2.42	0.139	1.57	0.228	0.01	0.943	2.08	0.168
		POPSIZE*MUTPRO	0.01	0.911	1.47	0.242	0	0.994	3.28	0.089
		MAXGEN*XOVER	2.85	0.111	0.57	0.46	0.25	0.623	0.49	0.493
		MAXGEN*TOURN	1.8	0.198	1.44	0.248	2.69	0.12	0.74	0.404
		MAXGEN*MUTPRO	4.06	0.061	5.03	0.04	1.33	0.265	6.94	0.018
		XOVER*TOURN	0.21	0.65	0.51	0.484	1.34	0.264	0.03	0.859
		XOVER*MUTPRO	0	0.99	0.01	0.906	1.26	0.278	0.3	0.592
		TOURN*MUTPRO	1.7	0.21	0.07	0.79	1.27	0.277	0.45	0.513
		Error	89913965		150052248		4.4		1061089696	

Appendix D3 – Table 9 Summary of analysis: OOBF with RotChr on (Gene 8 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	57.63	0	50.91	0	393.24	0	46.4	0
		MAXGEN	11.9	0.003	7.34	0.015	2.1	0.166	8.1	0.012
		XOVER	5.19	0.037	2.95	0.105	5.47	0.033	0.85	0.369
		TOURN	0.35	0.56	0.02	0.896	1.65	0.217	0.02	0.878
		MUTPRO	1.86	0.192	7.96	0.012	0.07	0.8	6.79	0.019
	Interactions	POPSIZE*MAXGEN	0.21	0.65	1.28	0.274	1.52	0.236	1.53	0.234
		POPSIZE*XOVER	2.59	0.127	0.49	0.493	4.75	0.045	0.12	0.729
		POPSIZE*TOURN	0.12	0.734	0.71	0.41	0.25	0.624	0.39	0.539
		POPSIZE*MUTPRO	0.04	0.851	0.88	0.362	0.06	0.809	0.74	0.402
		MAXGEN*XOVER	1.87	0.19	2.07	0.169	0.21	0.654	1.78	0.2
		MAXGEN*TOURN	0.06	0.815	0.12	0.736	0.37	0.551	0.04	0.852
		MAXGEN*MUTPRO	0.21	0.652	4.57	0.048	0.08	0.776	4.96	0.041
		XOVER*TOURN	3.49	0.08	7.73	0.013	0.55	0.467	7.22	0.016
		XOVER*MUTPRO	0.1	0.752	0.02	0.881	0.29	0.599	0.55	0.468
		TOURN*MUTPRO	0.5	0.49	0.39	0.541	2.71	0.119	0.07	0.79
		Error	309349826		261651170		23.905		2063626053	

Appendix D3 – Table 10 Summary of analysis: OOBF with RotChr on (Gene 9 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	186.5	0	68.49	0	114.5	0	51.29	0
		MAXGEN	70.77	0	15.23	0.001	4.15	0.058	6.85	0.019
		XOVER	14.57	0.002	6.89	0.018	7.86	0.013	5.82	0.028
		TOURN	0.3	0.592	0.48	0.499	0.7	0.415	0.81	0.381
		MUTPRO	1.65	0.217	1.81	0.197	0.08	0.778	2.02	0.174
	Interactions	POPSIZE*MAXGEN	28.53	0	6.8	0.019	0	0.982	2.36	0.144
		POPSIZE*XOVER	0.55	0.469	0.4	0.535	0.66	0.427	0.67	0.425
		POPSIZE*TOURN	0.29	0.6	0.02	0.896	0.96	0.341	0	0.956
		POPSIZE*MUTPRO	1.85	0.192	2.53	0.131	0.03	0.872	1.36	0.26
		MAXGEN*XOVER	0.34	0.566	0	0.973	0	0.971	0	0.954
		MAXGEN*TOURN	0.28	0.605	0.06	0.813	0.14	0.716	0.06	0.803
		MAXGEN*MUTPRO	0.02	0.898	0	0.986	0	0.97	0.05	0.823
		XOVER*TOURN	2.1	0.167	3.28	0.089	0.03	0.86	2.81	0.113
		XOVER*MUTPRO	1.09	0.313	0.23	0.639	0.79	0.387	0.64	0.436
		TOURN*MUTPRO	7.7	0.014	2.79	0.114	2.56	0.129	1.36	0.261
		Error	99641391		333383258		40.024		3381307564	

Appendix D3 – Table 11 Summary of analysis: OOBF with RotChr on (Gene 10 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	210.59	0	76.5	0	3.20E+04	0	44.42	0
		MAXGEN	91.12	0	34.23	0	9.9	0.006	18.09	0.001
		XOVER	6.86	0.019	3.14	0.096	0.07	0.794	1.49	0.24
		TOURN	3.26	0.09	5.74	0.029	1.74	0.206	4.5	0.05
		MUTPRO	20.92	0	24.82	0	0.14	0.714	16.72	0.001
	Interactions	POPSIZE*MAXGEN	36.05	0	12.41	0.003	1.68	0.214	3.5	0.08
		POPSIZE*XOVER	0.52	0.481	1.34	0.263	0.4	0.536	1.84	0.194
		POPSIZE*TOURN	3.87	0.067	2	0.176	1.24	0.283	1.32	0.268
		POPSIZE*MUTPRO	0.05	0.831	1.01	0.329	0.01	0.939	0.3	0.593
		MAXGEN*XOVER	1.65	0.217	2.56	0.129	0.82	0.378	3.26	0.09
		MAXGEN*TOURN	0.03	0.864	0.01	0.909	0	0.983	0	0.995
		MAXGEN*MUTPRO	1.27	0.276	0.22	0.647	0.23	0.637	0.28	0.602
		XOVER*TOURN	8.19	0.011	11.66	0.004	0.42	0.526	5.69	0.03
		XOVER*MUTPRO	2.47	0.136	1.17	0.295	0.08	0.782	0.88	0.361
		TOURN*MUTPRO	1.74	0.206	0.01	0.937	0.3	0.591	0.68	0.421
		Error	118254285		247288002		0.71		2444136154	

Appendix D3 – Table 12 Summary of analysis: OOBF with RotChr on (Gene 11 locked in first location) (GA optimisation case study).

			Mean		Std. Deviation		Larger-the-Better		Peak value	
			F	P	F	P	F	P	F	P
Full factorial	Main Factors	POPSIZE	148.71	0	72.52	0	182.13	0	64.57	0
		MAXGEN	62.38	0	25.88	0	0.52	0.482	17.78	0.001
		XOVER	5.57	0.031	2.08	0.169	0.47	0.505	0.36	0.559
		TOURN	0	0.976	0	0.979	0.04	0.838	0.01	0.921
		MUTPRO	0.19	0.667	0	0.984	0.26	0.62	0.08	0.787
	Interactions	POPSIZE*MAXGEN	23.9	0	8.61	0.01	0.66	0.43	3.17	0.094
		POPSIZE*XOVER	0.81	0.382	1.73	0.207	0.2	0.658	1.48	0.241
		POPSIZE*TOURN	1.32	0.267	0.08	0.778	0	0.959	0.01	0.944
		POPSIZE*MUTPRO	0	0.96	1.62	0.221	0.51	0.487	4	0.063
		MAXGEN*XOVER	2.72	0.119	3.24	0.091	0	0.963	3.82	0.068
		MAXGEN*TOURN	0.62	0.442	0.06	0.808	0.03	0.859	0.02	0.881
		MAXGEN*MUTPRO	3.25	0.09	1.02	0.326	0.06	0.816	0.67	0.424
		XOVER*TOURN	0.23	0.64	1.65	0.218	1.65	0.217	2.52	0.132
		XOVER*MUTPRO	1.32	0.267	0.02	0.887	0.01	0.913	0.02	0.888
		TOURN*MUTPRO	4.61	0.047	2.66	0.122	0	0.983	1.05	0.32
		Error	135779965		244880730		82.621		1647997089	

Appendix D3 – Table 13 Summary of analysis: OOBF with RotChr on (Gene 12 locked in first location) (GA optimisation case study).